ESSAYS ON THE COST STRUCTURE
OF
NONPROFIT NURSING HOMES

by

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To my grandmother, Nonna Maria

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Introduction

Increasing health care expenditures for the elderly population is a major concern for society and policymakers. In Europe, the percentage of people over 64 rose rapidly in the past decades and is expected to increase between two and six times by 2060, ranging from 22-25% in Belgium, Denmark, Ireland, and the United Kingdom, to 33-36% in Bulgaria, Germany, Latvia, Poland, Romania, and Slovakia. The share of very elderly people (80 and over) in the EU15 experienced the highest increase among all age classes, from 1.2% in 1950 to 4.2% in 2010, and is projected to almost triple (12%) by 2060 in the EU27 (Eurostat, 2012; European Union, 2012). Accordingly, the demand of nursing home care is expected to increase rapidly raising the burden on public resources generally used to cover nursing home costs or to subsidize prices of nursing home services (Karlsson et al., 2006).

Public provision of long-term care is increasingly challenging for governments. To ensure a sustainable system in the next decades, policymakers need evidence on the determinants of nursing care costs and how to best organize the sector to ensure efficient provision of care. This thesis aims at investigating issues regarding the cost structure of non-profit nursing homes using sound economic theory and rigorous empirical methodologies. The analysis focuses on Switzerland, where relatively high quality standards are sought through tight regulation, both on costs and quality aspects, and virtually no competition exists between nursing homes care providers. Nevertheless, the performance of non-profit nursing homes is still unclear and additional effort is necessary to increase the understanding of their behavior.

The first chapter of this thesis investigates the impact of different forms of organizations on the cost efficiency of non-profit nursing homes. We propose a model where the institutional form is represented by a legal constraint which affects managers in the decision-making process. Considering a sample of 45 Swiss Italian nursing homes over a 5-years period (2001-2005), we then disentangle persistent inefficiency due to differences in the institutional form from unobserved heterogeneity. The applied estimation strategy provides more accurate estimates of the impact of the institutional form on nursing homes efficiency, as compared to previous studies. Our empirical investigation does not find strong evidence of systematic differences between non-profit institutional forms providing nursing home care.

The second chapter analyses the impact of prospective payments on costs of nursing home care services. We sketch a simple theoretical model to predict the behavior of nursing homes under different payment schemes. We then investigate the implications of prospective payments on nursing home costs using a panel of 41 homes in Switzerland observed over a 10-years period (2001-2010). To evaluate the impact of the recent policy change - from retrospective to prospective payment - on nursing home costs, we adopt two empirical approaches: i) we estimate a model using a fixed-effects estimator (FE) with a time trend that is allowed to change after the policy reform; ii) we use a counterfactual approach (CF) where a fixed-effects model is used to predict costs for the years after the reform, and calculate the impact of the reform as the difference between observed- and predicted costs in each year. We find evidence that the new payment system reduces costs for nursing home care, *ceteris paribus*.

The third chapter focuses on the relationship between costs and quality in non-profit nursing homes. In the wide literature on NH costs, quality of care has been only marginally discussed. Most of the studies do not include measures of quality. Some of them rely on imprecise or indirect measures of quality, such as the number of deficiency citations. From an empirical point of view, failure to account for quality in cost functions is known to lead to omitted variable bias. To study the relationship between costs and quality, we use data on the clinical indicators derived from the Minimum Data Set. These quality indicators meet the taxonomy of the Structure-Process-Outcome (SPO) framework to measure quality in health care suggested by Donabedian (1988). As with respect to previous studies, we control for unobserved characteristics that may bias the relationship between costs and quality. We estimated a fixed effects model using a panel data of 45 nursing homes over a 4-years period. We find evidence of a positive relationship between quality of outcome,

measured by the prevalence of severe pain and weight loss, and costs. Also, higher staffing levels are correlated with higher costs. The institutional setting in which nursing homes operate is such that endogeneity of quality is unlikely. Nevertheless, as robustness check for potential endogeneity, we use information about residents' empowerment as instruments for quality indicators. Unfortunately, due to weak instruments, we are not able to empirically exclude endogeneity of quality.

Keywords: *nursing home costs, nonprofit, institutional form, prospective payment system, quality*

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List of Abbreviations

CPI	....	Consumer Price Index
DEA	....	Data Envelopment Analysis
FD	....	First-Difference
FE	....	Fixed Effects
GLS	....	Generalized Least Squares
GMM	....	Generalized Methods of Moments
MDS	....	Minimum Data Set
NFP	....	Not-For Profit
NH	....	Nursing Home
OLS	....	Ordinary Least Squares
PPS	....	Prospective Payment System
RAI	....	Resident Assessment Instrument
RDPH	....	Regional Department of Public Health
RE	....	Random Effects
RPS	....	Retrospective Payment System
SFr.	....	Swiss Francs
SPO	....	Structure-Process-Outcome
2SLS	....	Two-Stage Least Squares

Chapter 1

Does institutional form matter? An analysis of cost efficiency within the nonprofit nursing home sector

1.1 Introduction

As population ages the need for nursing home care increases (European Commission, 2008). Efficient and sustainable provision of nursing home care requires evidence on how to best organize the sector. Consequently, the influence of different organizational structures on nursing homes (NHs) efficiency is a relevant issue in most health care systems. The underlying idea is that the organizational structure affects the behavior of managers, therefore the performance of NHs.

In many countries NH services are mostly provided by regulated nonprofit firms (NFP). According to their ownership type, NFP NHs are usually categorized into *public* and *private* NHs. Although these types are supposed to reflect differences in the control of funds and the production process, the classification may not capture well differences in the organizational structure. A more sophisticated insight looks at the institutional form, which underlines property rights or legal constraints affecting different institutions. Hence, *public-law* NHs are public administrative units without a separate juridical status from the local public administration and are directly integrated into it. The governing body is represented by local politicians (city council), while the executive arm is left to the municipality, which delegates it to a manager. Conversely, *private-law* NFP NHs usually take the form of a foundation. Generally, foundations are created by natural persons or private legal entities. In some cases, the local governments may decide to create a private-law NFP NH. Therefore, when local governments set up a foundation to provide nursing home services, this is a private-law institution owned by the government. In both these cases the governing body is the foundation council.

As the need for long-term care increases, local governments have to choose among different ownership types and institutional forms to deliver nursing home services. Although the choice of the ownership type has received considerable attention in the recent research literature, little is known on the performance of different institutional forms which delineates the subject of this chapter. This study contributes to the literature on corporatization process of companies, a fairly common phenomena both in Europe and in the U.S. (Klien, 2012; Shleifer and Vishny, 1994).

The decision-making process may vary across organization forms, for instance because of different legal constraints or political pressure. Worthington and Dollery (2000) speak of local government managers as being "constrained by a host of non-discretionary factors in arriving at efficient outcomes". Hart, Schleifer and Vishny (1997) see public managers as being constrained by some government agreement to implement any cost innovation decision while managers of private NFP firms can freely implement these decisions. In addition, these firms are expected to face lower probability to be bailed out by public authorities or tougher punishment for poor managerial effort. Differences in the institutional form may then lead to differences in the efficiency of NHs. However, behavioral differences between institutional forms may be mitigated in highly regulated systems, such as the Swiss nursing home sector (cfr. section 1.2.1).

The issue of institutional forms efficiency in nursing home care has received a partial answer in the economic literature so far. The focus is mainly on the effects of the ownership by comparing for-profit and not-for-profit organizations. Government-run organizations have been typically excluded from the analyses due to the small presence of public facilities in the U.S. or due to the fact that government NHs are expected to behave in a very different way than for-profit and NFP NHs (Ferguson, 2002; Grabowski et al., 2013). These studies show that for-profit NHs are more efficient than nonprofit NHs but provide lower quality services (Schlesinger and Grey, 2006; Knox et al., 2003; O'Neill et al., 2003; Hillmer et al., 2005). However, there is lack of evidence on differences between public-law and private-law NFP organizations.

Kapur and Weisbrod (2000) recognize that government and private NFP firms do differ in their objective functions. To our knowledge, only few studies (e.g. Farsi and Filippini, 2004; Farsi et al., 2008) analyze the impact of the institutional form on the performance of NFP NHs. Farsi and Filippini (2004) estimate a random effect model with time-invariant inefficiency as proposed by Schmidt and Sicklers (1984) using Swiss data. The authors show that private-law NHs are more efficient than public-law NHs. The study has two main drawbacks. First, given the length of the panel, the assumption of time-invariant inefficiency may not be appropriate. Second, the results can be biased in the presence of unobserved factors that remain constant over time since the individual effects are interpreted as inefficiency. To tackle these aspects, Farsi et al. (2008) estimate inefficiencies based on a true random effect model (TRE). The authors do not find significant differences between institutional forms. Although the new approach allows for time-varying inefficiency and controls for unobserved heterogeneity, constant inefficiency is captured by the individual effects rather than being included in the traditional inefficiency term. This may lead to incorrect results if part of the inefficiency is due to some features that do not change over time, such as the institutional form.

In this chapter, we hypothesize that there are two types of inefficiency: a persistent, institutional form-related component, and a time-varying part related to managerial skills. The institutional form cannot be controlled by the manager but defines organizational differences between NHs, which affects the managerial decision process. To capture structural differences due to the institutional form, we incorporate a dummy variable directly into the deterministic part of the cost frontier and estimate a TRE model. This methodology allows us to purge the individual effects from the impact of the institutional form, which can then be added to the traditional time-varying inefficiency estimator.[1]

The remainder of the chapter is organized as follows. In section 1.2 we sketch a theoretical model of managerial behavior in NHs and derive hypotheses on the impact of different institutional forms on cost efficiency. In section 1.3 we present the empirical analysis and the data. Section 1.4 discusses the methodology used to validate the hypotheses derived in section 1.2.4. Section 1.5 summarizes the results and suggests some policy implications of our analysis. Section 1.6 concludes.

1.2 The model

1.2.1 Institutional setting

This study focuses on highly regulated NH sectors largely dominated by nonprofit institutions, akin to the Swiss nursing home care sector. In Switzerland the provision of NH services is organized at the cantonal level. In some cantons this is further decentralized at the municipality level. In these cases, one NH provides care to the residents of a predefined catchment area. Prices are subsidized by the cantonal regulator, leading to excess of demand and long waiting lists. Consequently, the choice of the NH does not depend on price and quality aspects and NHs generally operate as local monopolies.

In the Swiss region (Ticino) considered in this analysis, around 51% of NFP NHs are private-law NFP organizations, public-law NHs represent 49% of the market. Finally, a small percentage of the market (5%) is served by for-profit NHs. These are subject to different regulation and data are not available.

To capture the behavior of public-law and private-law NFP NHs, we draws from studies that model the bargaining process between the management and the ownership (e.g. Schmitz, 2000) and the management and workers (e.g. Glaeser, 2002). Similarly to Haskel and Sanchis (1995), we sketch a model where low managerial effort translate into low efficiency levels. The governing board of the NH (G) can take two different institutional forms:

[1] Note that this approach does not rule out differences between institutional forms that vary over time since these are eventually captured by the time-varying component.

public-law ($i = Pu$) or private-law NFP ($i = Pr$). A Manager (M) runs the organization and a regulator (R) defines the financial resources for the NH. The total costs of the NH are described by the following equation:

$$C_i = \theta - \alpha_i e. \tag{1.1}$$

The first term to the right hand side of equation (1.1), θ, is a structural parameter defining costs that are independent from managerial effort and only partially observable by the regulator. This parameter depends, for instance, on the severity mix of patients, the number and quality of professional staff members, or the location of the NH. Costs include a fixed remuneration for the manager (W). For simplicity, we assume that θ is a random variable which takes only two values: $\underline{\theta}$ and $\overline{\theta}$, with $\overline{\theta} > \underline{\theta}$. The probability that $\theta = \underline{\theta}$ and $\theta = \overline{\theta}$ is q and $(1 - q)$ respectively. The last term in the equation, e, is the manager's effort to reduce total costs. The parameter $\alpha_i \in (0, 1)$ reflects the effectiveness of managerial effort, i.e. the marginal impact of effort on costs. This parameter varies with the institutional form of the NH and represents a constraint on managers' autonomy in the decision-making process. The parameter α_i can also be interpreted as the impact of bureaucratic decision-making processes.

In Switzerland, NHs are local monopolies and the demand for NH services is likely to be independent from actions undertaken by other facilities. We normalize to one the population of patients in each market area. Therefore, equation (1.1) can also represent the average cost per patient. In practice, part of the cost is covered through user charges which depend on the wealth of the elderly. Though, fees do not differ by institutional form and are therefore neglected in the model.

Costs are observed at the end of the year by the regulator when NHs deliver the yearly report. However, the regulator cannot distinguish between structural costs and the impact of managerial effort. An ex-ante budget is applied to finance NHs based on the following rule:

$$B = q\underline{\theta} + (1-q)\overline{\theta} = \widehat{\theta}. \tag{1.2}$$

The regulator knows the mean and the variance of the distribution of the structural cost parameter. Though, the realization of θ for a given NH is unknown. Hence, the regulator can only set a budget based on the weighted average of the structural parameters.

1.2.2 Nursing homes objectives

The behavior of NHs is defined by the interaction between the board and the manager. The utility function of the board is given by the following equation:

$$U_{G_i} = S_i - \lambda_i^{\theta}(B - C_i)^2, \tag{1.3}$$

where S_i represents exogenous benefits from the production of NH services that may also vary with the institutional form.[2] Disutility from an unbalanced budget is a quadratic function which also varies with the institutional form, with $\lambda_{Pu}^{\theta} < \lambda_{Pr}^{\theta}$, and $\lambda_i^{\theta} \in (0,1)$ captures the impact of deviations from an unbalanced budget. Note that unbalanced budgets generate a disutility both if financial resources are greater than costs and vice versa. This is because the fund-raising activity to match the lack of resources is costly. Also, an excess of financial resources is detrimental since these resources cannot be retained. Within the Swiss Italian budgeting system, NHs are required to pay back the regulator the remaining resources at the end of the year.[3] This means that, not only efficient NHs are not rewarded for their effort in controlling costs, but there is also a perverse incentive to spend all the budget obtained from the regulator. Consequently, NHs maximize their objective function when the budget is balanced.[4] Moreover, since disutility from unbalanced budget is likely to be higher when financial resources are lower than costs than vice versa, we allow

[2] For example, the board of a public-law NH may value the preferences of the whole voters' community while a private-law NFP board may value those of the donors or of particular groups of interest.

[3] The performance of the NH is verified at the end of the year based on the accounting report delivered to the regulator.

[4] The nonprofit literature is rich of models following this approach (e.g. Zweifel et al., 2009).

for non-uniform disutility and assume $\lambda_i^{\overline{\theta}} \geq \lambda_i^{\underline{\theta}}$.[5]

We can now turn to the objectives of the manager. The manager's utility can be defined by the following expression:

$$U_{M_i} = W - \phi_i(e) + \gamma_i U_{G_i}, \tag{1.4}$$

where W is the manager's wage, $\phi_i(e)$ is disutility of effort, and $\gamma_i \in (0,1)$ is the degree the goals of the board are internalized by the manager. Substituting for U_{G_i} in (1.4), the marginal impact of an unbalanced budget on manager's utility is $\gamma_i \lambda_i$.

The manager's utility is additive in effort and the degree of sharing of the board's objectives, with $d\phi/de > 0$ and $d^2\phi/de^2 > 0$. We hypothesize that the disutility of effort takes the form $\phi_i(e) = \frac{\eta}{2}e^2$, with $\eta > 0$. The marginal impact of effort on manager's utility is then captured by the parameter η. In the following analysis, we assume that disutility of managerial effort does not vary across institutional forms. In Switzerland, work contracts for managers are highly regulated by the law and cannot differ by institutional form. Nevertheless, non-explicit conditions may imply that managers working for public-law NHs are subject to lower risk of losing their job when the effort is not satisfactory.[6]

Finally, the level of effort is bounded to take a value in the interval $e \in [0, e_{max}]$, where $e_{max} = \frac{q}{\alpha_i}(\overline{\theta} - \underline{\theta})$.[7] For simplicity, the reservation utility is assumed to be zero so that the participation constraint of the manager is always satisfied for any level of the wage.

[5] Note that for $\theta = \underline{\theta}$ we have $B - C_i > 0$ (*over financing*) for any level of effort e. Conversely, for $\theta = \overline{\theta}$, we have $B - C_i \leq 0$ (*under financing*) for any $e \in [0, e_{max}]$. See Section 2.2 for further details.

[6] In a separate exercise, we allowed for heterogeneous disutility of effort across institutional forms. We hypothesized that $\eta_{Pu} \geq \eta_{Pr}$, i.e. the cost of effort is higher for managers in public-law NHs than for managers in private-law NFP NHs. The main results are unchanged.

[7] This ensures that the manager can decrease costs up to the level where $B = C$. Beyond this level, more effort would reduce the utility of the manager since a higher level of effort produces resources that cannot be exploited.

1.2.3 Managerial effort

The optimal choice of effort for the manager is obtained from the first-order conditions to maximize (1.4) under two possible scenarios: over financing ($\theta = \underline{\theta}$) and under financing $\left(\theta = \overline{\theta}\right)$. Remember that the budget is defined by the regulator as a weighted average of the structural cost parameter (1.2). Using (1.1) and (1.2), we then observe that for $\theta = \underline{\theta}$ we have $B - C_i > 0$ for any level of effort e. Conversely, for $\theta = \overline{\theta}$, we have $B - C_i \leq 0$ for any $e \in [0, e_{max}]$. To write the first-order conditions for the two scenarios, we first substitute (1.1) and (1.2) into (1.3). Using (1.3) we then replace U_{G_i} in (1.4), and finally derive (1.4) for the level of effort to get:

$$\frac{dU}{de}|_{\theta=\underline{\theta}} = -\eta e - 2\alpha_i\gamma_i\lambda_i^{\underline{\theta}}\left[\alpha_i e + (1-q)(\overline{\theta} - \underline{\theta})\right] \leq 0, \tag{1.5}$$

$$\frac{dU}{de}|_{\theta=\overline{\theta}} = -\eta e - 2\alpha_i\gamma_i\lambda_i^{\overline{\theta}}\left[\alpha_i e + q(\underline{\theta} - \overline{\theta})\right] = 0. \tag{1.6}$$

Solving the two equations we get the equilibrium levels of effort as:

$$e^* = \begin{cases} 0 & : \quad \theta = \underline{\theta} \\ \frac{\alpha_i\beta_i q\left(\overline{\theta}-\underline{\theta}\right)}{\eta+\alpha_i^2\beta_i} & : \quad \theta = \overline{\theta} \end{cases}, \tag{1.7}$$

where $\beta_i = \gamma_i\lambda_i^{\overline{\theta}}$. Note that for $\theta = \underline{\theta}$, the manager has no incentive to make a positive effort. This is because any positive level of effort would increase economic profits which cannot be retained by the firm. Conversely, for $\theta = \overline{\theta}$, a positive level of effort is valuable to reduce losses. The optimal level of effort clearly depends on the magnitude of the difference between high structural costs ($\overline{\theta}$) and low structural costs ($\underline{\theta}$).

1.2.4 Model predictions

From eq. (1.7) above, note that managerial effort varies according to the type of productivity constraint of NHs defined by the institutional form ($i = Pu, Pr$). Given the features of the funding system, there are no behavioral differences between the two institutional forms if NHs are generally over financed, i.e. if $\theta = \underline{\theta}$. In this case, the choice of effort does not depend on the institutional form-specific parameters. Therefore, we focus on the choice of effort when $\theta = \overline{\theta}$, i.e. when NHs incur a loss or just cover costs. Managerial effort depends on the marginal disutility of a loss (λ_i) and the importance of the board's objectives (γ_i), which is captured by the parameter β_i. Finally, managerial effort depends on the marginal impact of manager's effort on costs (α_i).

Looking at the comparative static properties of the equilibrium in the case of under-financing, we can shortly discuss how the other parameters of interest affect the optimal choice of effort. For $\theta = \overline{\theta}$, we get:[8]

$$\frac{de^*}{d\alpha_i} \begin{cases} > 0 & : \quad \alpha_i < \frac{\eta}{2\beta_i} \\ \leq 0 & : \quad \text{otherwise} \end{cases}, \tag{1.8}$$

The optimal level of effort exerted by the manager increases for low levels of α_i and decreases when α_i is relatively high. Since α_i represents the marginal impact of effort on costs, eq. (1.8) implies that a higher level of effort is required to cover costs when the marginal impact of effort is relatively low, given the marginal disutility of an unbalanced budget and the degree the goals of the board are internalized (β_i) and the marginal cost of effort for the manager (η).

As for the impact of β_i, we have $de^*/d\beta_i > 0$.[9] Therefore, higher marginal impact of unbalanced budgets on managers' utility (β_i) leads to higher levels of managerial effort in equilibrium. Since $\beta_i = \gamma_i \lambda_i^{\overline{\theta}}$ with both γ_i and $\lambda_i^{\overline{\theta}}$ positive and lower than 1, we also conclude that $de^*/d\gamma_i > 0$ and $de^*/d\lambda_i^{\overline{\theta}} > 0$. Higher levels of effort in equilibrium derive from higher degrees of goals sharing (γ_i) and higher disutility of the board from unbalanced budgets ($\lambda_i^{\overline{\theta}}$). Finally, from (1.8) we get $de^*/d\eta < 0$ which implies that a higher marginal cost of effort for the manager decreases the equilibrium level of effort to reduce costs, as

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[8] By deriving (1.7) for $\theta = \overline{\theta}$ with respect to α_i we get $\frac{de^*}{d\alpha_i} = \frac{\beta_i q(\overline{\theta}-\theta)(\eta-\beta_i\alpha_i^2)}{(\eta+\beta_i\alpha_i^2)^2}$. This is positive if the last term at the numerator is positive, which leads to (1.8).

[9] Deriving (1.7) for $\theta = \overline{\theta}$ with respect to β_i, we obtain: $\frac{de^*}{d\beta_i} = \frac{\alpha_i \eta q(\overline{\theta}-\theta)}{(\eta+\beta_i\alpha_i^2)^2}$ which is always satisfied.

expected.

Previous studies suggest that parameters α_i and β_i differ across institutional forms. Likely, $\alpha_{Pu} < \alpha_{Pr}$ and $\beta_{Pu} < \beta_{Pr}$. The first parameter of interest, α_i, is a key factor in our analysis. It seems plausible that governmental boards put more bureaucratic curbs on the management decisions than boards of private-law organizations (foundations). This leads to higher marginal costs of innovations to reduce costs and, therefore, to less effective managerial effort (lower α_i). This argument has already been recognized by other authors, for instance Worthington and Dollery (2000). Yet, despite this hypothesis, tight regulation may mitigate differences across institutional forms.

The second parameter of interest, β_i, refers to the marginal impact of an unbalanced budget on manager's utility. This impact is expected to be higher in the case of private-law NFP NHs for two reasons. First, private-law NFP NHs face higher fund-raising costs as compared to public NHs (Kornai, 1980; Duggan, 2000). This is because the local government is likely to cover costs of public-law NHs that exceed the resources allocated by the regulator. Second, the degree to which managers working in private-law NFP NHs share the objectives of the council is expected to be higher, or at least equal, than that of managers working in public NHs. This statement relies on factors suggested by different authors in the literature (Rose-Ackerman, 1996; Lakdwalla and Philipson, 1998; Wilson, 1989). Managers working in foundations are expected to be more likely to be driven by altruistic motives and to be punished in case of poor performance, and are less likely to follow multiple objectives with which the manager may not agree. Similar expectations apply to the present case. In particular, private-law NFP NHs are motivated by specific goals and are more likely to be punished in the case of poor performance (e.g. lower bailing out probability). Private-law NFP NHs may also be subject to the interest of particular groups of stakeholders.

To summarize, the model suggests that the behavior of NHs varies with the institutional form. In the case of under financing, the utility-maximizing effort of managers in private-law NFP NHs is likely to be higher than the effort of managers in public-law NHs, which may lead to higher efficiency in private-law NFP NHs. To empirically investigate the issue, we specify a cost function for a sample of public-law and private-law NFP NHs and compare their cost efficiency.

1.3 Empirical specification and data

1.3.1 Detailing the cost function

Previous studies using Swiss data (Filippini, 1996; Crivelli et al., 2002; Farsi et al., 2005; Farsi et al., 2008) analyze the NH production process specifying a two inputs cost function with capital and labor. The price of capital is derived from the residual approach, i.e. taking the difference between total costs and labor costs divided by the number of beds. This specification does not reflect differences that may arise in room and food quality, which are two important aspects of nursing home care. Consequently, misspecification may lead to biased estimated inefficiencies. In this study we propose a better measure of capital price and include a third input price, called "material price", to control for food and lodging differences. We assume that NHs transforms three inputs - capital, labor and material - into a single output, measured by the number of patient-days of nursing care.[10] Strategic interactions among NHs and their effect on the demand of residents is ruled out as NHs are local monopolies. The number of patient-days can be considered a good indicator of the level of production after controlling for differences in quality. The total costs function depends on output (Y), the prices for labor, capital and material (P_l, P_k, P_m), two output characteristics (Q_1, Q_2), a dummy variable (IF) which takes value equal to 1 for public-law

[10] Output and input prices are assumed to be exogenous. Output is exogenous because NHs have to accept all residents in a given area. The price of labor is defined by labor contract at the cantonal level, and are equal for all NHs in the sample. Also, the same amortization schedule and interest rates are applied.

NHs and 0 otherwise, and a time trend (τ) which captures technological progress:[11]

$$C = f(Y, P_l, P_k, P_m, Q_1, Q_2, IF, \tau). \tag{1.9}$$

The price of labor is calculated as the weighted average wage of different professional categories employed in the NH (doctors, nurses, administrative and technical staff) to avoid multicollinearity problems that may arise with labor prices for different categories. The amount of staff as well as their certification is defined by the cantonal law as a function of residents' case-mix. This rules out the possibility of increasing cost efficiency by hiring lower certified nurses.[12] The price of capital is calculated as the sum of mortgage costs, amortization and costs related to capital purchases divided by the capital stock, which is approximated by the number of beds. The price for material is computed by taking the remaining costs and dividing them by the number of meals provided each year. This item mainly includes costs for food and residency. Other costs included are energy, water and administrative costs.

Additionally, we control for some output characteristics that may explain cost differences across NHs.[13] Q_1 is an index which measures average patients' assistance need by means of normal daily activities such as eating, personal care or physiological activities. This is calculated on a yearly basis by the Regional Department of Public Health (RDPH). Patients are classified in one out of five categories according to their severity level. A value between 0 and 4 is assigned where higher values indicate more severe cases.

Q_2 is the nursing staff ratio, that is the ratio between the number of nurses employed

[11] In a non-competitive environment such as the Swiss one, there is no reason to assume that NHs minimize costs. In this case, the estimated costs function is a "behavioral cost function" (Evans, 1971) and can still be used to make a comparison among firms. Moreover, by estimating a total costs function instead of a variable costs function we avoid the risk related to a possible high correlation between capital stock and output leading to a positive relationship between variable cost and capital stock (Filippini, 1996).

[12] The monetary compensation of the staff is also a function of age. Therefore, there exists the possibility to reduce costs by hiring younger staff members. Due to lack of data, we cannot rule out this strategic behavior.

[13] In order to estimate a cost function, either the output is assumed to be homogenous or we need to control for service intensity and patients' characteristics (Birnbaum et al., 1981).

and the number of nurses that should be employed according to the guidelines of the RDPH (optimal amount of staff).[14] Because nursing care is a labor-intensive service, staffing level has been recognized as a good indicator for quality.[15] Consequently, the nursing staff ratio is regulated by the RDPH. To avoid worsening quality, NHs are not allowed to deviate from the suggested amount of nurses by more than ±10%. Since labor cost represents the major cost of production (cfr. section 3.2), a small change in the nursing staff ratio may affect total cost considerably. For this reason, NHs with high costs may decide to decrease the proportion of workers. On the other hand, efficient NHs may hire new workers or increase the working time to justify additional costs to the regulatory authority. The endogeneity of the nursing staff ratio is confirmed by the robust Durbin-Wu-Hausman test performed using the lagged Q_2 as instrumental variable (Cameron and Trivedi, 2005). The null hypothesis of exogenous Q_2 is rejected at any standard levels of significance. To address the endogeneity problem, lagged values of the nursing staff ratio (Q_2L) are used.[16] Given that Q_2 is determined during the operating year (for example through flexible working time) while the budget is defined at the beginning of the year, the lagged value of Q_2 is expected to be a valid instrument.[17]

The dummy variable IF captures differences across institutional forms, as hypothesized in section 2. This variable can be assumed to be exogenous for two main reasons. First, organizational form differences are mainly driven by historical reasons. Precisely, nursing home care was initially provided by religious foundations. Later, increasing demand of NH

[14] As compared to other quality indicators related to staffing levels, our indicator is conceptually different. The nursing staff ratio is the deviation from the optimal number of nurses that should be employed according to guidelines of the regulator rather than the number of staff nurses employed.

[15] In a recent review, Bostick et al. (2006) show a positive association between staffing levels and quality of care, and the link between staffing levels and direct indicators of quality, such as functional ability, pressure ulcers and weight loss.

[16] This is a rather simple approach to tackle endogeneity in frontier analysis where other solutions, such as 2SLS, are not feasible.

[17] The output of the test statistic on the endogeneity of Q_2 is: $F(1, 44) = 11.52$ ($p = 0.002$). The endogeneity test is performed on the cost model with first order coefficients. The statistics provided gives some evidence that the lagged value is a valid instrument. The first stage regression summary indicates that the lagged value explains 40% of the variability in Q_2. The Stock and Yogo test at 5% level of tolerance greatly rejects the null hypothesis of weak instrument (F=80.57 >16.38). The same analysis performed on the two-years lagged value of Q_2 suggests that this instrument is likely to be weak.

care and lack of supply led local governments to build new NHs. Second, NHs changing institutional form are not allowed to benefit from financial advantages.

In order to impose as few restrictions as possible, we adopt a flexible translog functional form approximated at the median value, a less sensitive statistic to outliers than the mean. Input prices and total costs are divided by the material price to satisfy the homogeneity condition in input prices.[18] The stochastic translog approximation to (1.9) is:

$$\begin{aligned}
&\ln\left(\frac{C}{P_m}\right) = \delta_0 + \delta_Y \ln Y + \delta_{Q_1} \ln Q_1 + \delta_{Q_2} \ln Q_2 L + \delta_{P_l} \ln \frac{P_l}{P_m} \\
&+ \delta_{P_k} \ln \frac{P_k}{P_m} + \frac{1}{2}\delta_{YY}(\ln Y)^2 + \frac{1}{2}\delta_{Q_1Q_1}(\ln Q_1)^2 + \frac{1}{2}\delta_{Q_2Q_2}(\ln Q_2 L)^2 \\
&+ \frac{1}{2}\delta_{P_lP_l}\left(\ln \frac{P_l}{P_m}\right)^2 + \frac{1}{2}\delta_{P_kP_k}\left(\ln \frac{P_k}{P_m}\right)^2 + \delta_{YQ_1} \ln Y \ln Q_1 \\
&+ \delta_{YQ_2} \ln Y \ln Q_2 L + \delta_{YP_l} \ln Y \ln \frac{P_l}{P_m} + \delta_{YP_k} \ln Y \ln \frac{P_k}{P_m} \\
&+ \delta_{Q_1P_l} \ln Q_1 \ln \frac{P_l}{P_m} + \delta_{Q_1P_k} \ln Q_1 + \ln \frac{P_k}{P_m} + \delta_{Q_1Q_2} \ln Q_1 \ln Q_2 L \\
&+ \delta_{P_lQ_2} \ln \frac{P_l}{P_m} \ln Q_2 L + \delta_{P_kQ_2} \ln \frac{P_k}{P_m} \ln Q_2 L + \delta_{P_kP_l} \ln \frac{P_k}{P_m} \ln \frac{P_l}{P_m} + \\
&+ \delta_{IF} IF + \delta_t \tau + \varepsilon,
\end{aligned} \tag{1.10}$$

where ε is the composite error term defined in Table 1.3. The individual subscript i and the time subscript t are omitted for simplicity.

1.3.2 Data and descriptive statistics

Our study exploits an unbalanced panel data set of 50 NHs operating in a region of Switzerland (Canton Ticino) over a 5-years period (2001-2005).[19] All NHs in the sample are medicalized institutions (skilled NHs) under the cantonal NH planning. The cantonal planning

[18] The cost function is linear homogenous of degree 1 in input prices when a 10% increase in all input prices leads to a 10% increase in total cost.

[19] Data are available until year 2010. However, in 2006 a new financing system was introduced. This change may have affected the relative efficiency of different institutions. Consequently, we excluded the period 2006-2010 from the present analysis. The impact of the new reform on the performance of NHs is analyzed in chapter 2 of this thesis.

defines daily rates, the minimum necessary infrastructure, and the amount and certification of staff based on residents' needs to ensure high quality standards. It also defines supply capacity in terms of beds, and subsidies to public-law and private-law NFP NHs. Consequently, the production process is highly homogenous and comparable across NHs.

Data are extracted from annual reports delivered to the RDPH by regulated NHs. NHs with foyers are excluded from our sample.[20] One NH shows unreasonable values, hence it is also excluded from the analysis.[21] The final sample contains data of 45 NHs, 22 private-law NFP NHs and 21 public-law NHs,[22] with a total number of observations equal to 210. Note that as compared to previous studies on Swiss NHs (e.g. Filippini, 1996; Farsi et al., 2005; Farsi et al., 2008), this dataset includes full information on the capital costs for public NHs that was previously not available.[23]

Table 1.1 presents the summary statistics for the main costs and input variables of interest: mean, standard deviation, median, minimum and maximum values for our sample. All input prices, total cost and variable cost are inflated to 2005 constant currency units (Swiss francs) using the national Consumer Price Index. The average cost per resident day in the most expensive NH is almost twice the average cost of the least expensive home, with an average of about 233 Swiss francs (SFr.). This difference is at least partially explained by the large heterogeneity in NHs characteristics. In particular, facilities vary in size. The number of beds ranges from a minimum of 28 to a maximum of 162, which leads to a high standard deviation also in the total annual resident days. Differences in case-mix characteristics are also remarkable: the average patient dependency index ranges from 0.8 to 3.8, even though mean and median values are very close. As expected, the nursing staff

[20] Foyers are external residential apartments where nursing care is provided to the most "in-health" patients. Since the production process may differ substantially, when a considerable share of patient-days is spent in foyers ($> 10\%$), these observations are dropped.

[21] This NH was initially a for-profit institution and, consequently, changed the regulation regime. Since for-profit NHs provide luxury residential services, their production process is hardly comparable with the production process of other homes.

[22] The reported number of NHs for each institutional form is the average number of homes over the whole period considered. The number of private-law NFP NHs ranges from 21 to 23, while public-law NHs vary between 20 and 22.

[23] These additional data on the amortization costs of public-law NHs have been made available just recently.

ratio is close to 1. In fact, NHs are supposed to follow the guidelines of the RDPH and to employ as many nurses as it is suggested. Large variations are finally observed for all input prices. The price of capital shows the greatest variation, mostly explained by investments made to renew the facility. The labor price shows the average yearly wage of the staff and varies between SFr. 63000 and SFr. 94000. The mean price for meals is SFr. 8.40 and ranges between SFr. 5 and SFr. 12. These reasonable values support our specification of material price. Labor costs represents 82% of total costs, whereas capital costs and material costs account for 6% and 12%, respectively.

Variables	Mean	Std. Dev.	Median	Min.	Max.
Average cost (SFr./resident day)	232.80	26.40	235.50	172.85	297.60
Total annual resident days (Y)	24032	9780	21911	9925	58324
Average dependency index (Q_1)	3.08	0.37	3.14	0.80	3.80
Nursing staff ratio (Q_2)	0.966	0.090	0.96	0.74	1.55
Average labor price in SFr. per employee per year (P_l)	80266	4817	80613	63363	93704
Average capital price in SFr. per bed (P_k)	5398	2671	4993	1054	22891
Average material price in SFr. per meal (P_m)	8.35	1.20	8.32	5.15	11.70
Number of beds	68	27	64	28	162

Notes: All monetary values are in 2005 Swiss francs (SFr.), adjusted by the national Consumer Price Index.

Table 1.1: Descriptive statistics of the main costs and input variables (N=210).

To focus on differences between private-law and public-law NHs, in Table 1.2 we report the mean and the standard deviation of the above variables separately for each subsample. In the last column of Table 1.2, we report the results of a two-sided t-test under the null hypothesis of equal means between the two groups. The statistics show that public-law and private-law NFP NHs are similar in many aspects, which also explains the similarity in observed mean costs per resident. NHs run under different organizational forms face similar residents and input prices. The only statistically significant difference lays in the average number of beds. Private-law and public-law NHs have respectively 59 and 77 beds on average, suggesting that public NHs may enjoy decreasing average costs (Farsi et al., 2008; Hoess et al., 2009). Regarding output characteristics, the two groups do not show significant differences in the nursing staff ratio nor in the case-mix. Although data do not show important differences between public-law and private-law NFP NHs, unobserved factors related to costs may still result in different performance. For example, Q_2 may capture only part of quality differences. Hence, NHs providing higher quality services than the average may perform better, *ceteris paribus*.

Variables	Private-law NHs (Pr)	Public-law NHs (Pu)	t-value
Average cost (SFr./resident day)	233.90	231.60	0.650
	(29.55)	(22.70)	
Total annual resident days (Y)	20755.80	27464.80	-5.342***
	(7252.45)	(10882.70)	
Average dependency index (Q_1)	3.104	3.071	0.659
	(0.369)	(0.371)	
Nursing staff ratio (Q_2)	0.969	0.963	0.512
	(0.111)	(0.062)	
Average labor price in SFr. per employee per year (P_l)	80068.70	80474.05	-0.616
	(4987.40)	(4647.10)	
Average capital price in SFr. per bed (P_k)	5451.20	5342.25	0.298
	(3369.30)	(1665.50)	
Average material price in SFr. per meal (P_m)	8.20	8.50	-1.630
	(1.25)	(1.13)	
Number of beds	59	77	-5.111***
	(21)	(30)	
Number of homes	22	21	-
Number of observations	110	100	-

Notes: Standard deviations are given in brackets. All monetary values are in 2005 Swiss francs (SFr.), adjusted by the national Consumer Price Index. Significance levels: * = 10%, ** = 5%, *** = 1%.

Table 1.2: Differences in mean costs and inputs among institutional forms.

1.4 Methodology

We investigate the effect of institutional form on the performance of NHs by applying three different econometric approaches. The first and the second approaches use stochastic frontier models. Both frontier methods estimate a benchmarking cost frontier against which the actual performance of the firms in the sample is compared. The main difference between the two frontier approaches lies in the way exogenous factors are treated in the analysis of efficiency.[24,25]

The first approach (Model 1) relies on the assumption that the institutional form affects the degree of inefficiency directly. The performance of each NH is measured in relation to a single best practice frontier and the impact of the institutional form on inefficiency is tested afterwards by means of the non-parametric Kruskal-Wallis test.

The second approach (Model 2) includes a dummy variable for the institutional form directly into the main cost equation and estimates two distinct best practice frontiers.[26] The rationale is that NHs with different institutional forms may face different operating environments and/or objectives. Consequently, they can adopt different combinations of inputs. The resulting inefficiencies are net of institutional characteristics (*net inefficiencies*) and are interpreted primarily as an indicator of managerial performance (Coelli et al., 1999). In the present case, net inefficiencies capture any difference between public-law and private-law NFP NHs related to time-varying factors. The distance between the actual costs and the group-specific best practice frontier provides information about the within-group inefficiency of private-law and public-law NHs. Conversely, the between-groups inefficiency is measured as the distance between the two frontiers, i.e. the coefficient of the dummy variable. Finally, by re-evaluating the traditional efficiency predictor with the formula applied by Coelli et al. (1999), all firms can be compared to the most favorable best practice frontier. This is achieved by multiplying the usual time-varying efficiency predictor (u_{it}) with the exponential of the estimated coefficient related to the institutional form dummy, here called (δ_{IF}), a measure of *gross inefficiencies*.

Finally, for robustness check in the third approach we apply "traditional" panel-data models, with particular focus on the potential correlation between the individual effects

[24] See Simar, Lovell, and Vanden Eeckaut (1994) for a review of approaches to include exogenous factors in efficiency measurement studies.

[25] The ideal situation to study differences due to the institutional form would be to compare institutions with same ownership form but different institutional forms; i.e. government-run NHs versus NHs owned by the local government but run as foundation (public foundations). However, due to the small sample size of public foundations NHs (6.7%), we are not able to use this identification strategy.

[26] A similar approach has been applied in the literature on hospital efficiency to study the impact of ownership (Grosskopf and Valdmanis, 1987) and size (Ozcan at al., 1998), although not combined with a TRE model.

and the covariates. In this approach we capture the impact of the institutional form on total costs with a dummy variable. Panel-data models and stochastic frontier models are conceptually not equivalent, in particular with respect to the output specified. The regression function specifies a conditional mean of output, instead the frontier counterpart defines the maximum output (minimum cost) available with a given set of inputs (prices) (Cornwell and Schmidt, 2008). As panel-data models rely on less assumptions, these can provide more conservative robustness check.

1.4.1 Stochastic frontier models

The parametric frontier approach includes many techniques; in particular the literature distinguishes between deterministic and stochastic methods. The main disadvantage of deterministic methods is that it is not possible to separate statistical noise from inefficiency, as any deviation from the frontier is interpreted as inefficiency. Hence, higher inefficiencies levels are expected when deterministic approaches are implemented as compared to stochastic frontier models. An overview of the stochastic frontier models for cross-sectional and panel-data models is shown in Appendix (Figure 1). More recent stochastic frontier models for panel data have introduced the possibility to further disentangle inefficiency and statistical noise from unobserved heterogeneity such as factors that are not under the control of the management (Murillo-Zamorano, 2004). In this study we opt for panel-data parametric methods to address the issue of unobserved heterogeneity.

For both stochastic frontier approaches described above, we estimate a pooled frontier and a true random effects model (TRE) developed by Greene (2005). The pooled frontier estimator, used for comparison purposes, considers the sample as series of cross sectional observations and assumes that the firm-specific effects are zero. It relies on the canonical cost model specification of Aigner, Lovell and Schmidt (1977) expressed in logarithms:

$$\ln\left(\frac{C_{it}}{P_{m,it}}\right) = \delta_0 + \sum \delta_s \ln X_{s,it} + v_{it} + u_{it}, \qquad u_{it} \geqslant 0 \tag{1.11}$$

where X_s is the vector of all explanatory variables s defined in 1.10. The composite error term is the sum of a symmetric, normally distributed term v_{it} capturing the statistical noise and a one-sided non-negative disturbance representing the inefficiency, u_{it} (cfr. Table 1.3). The estimation of this model provides estimates of the structural parameters δ_s. By plugging in the observations, it is possible to get estimates of the composed error term ε_{it}. The (in)efficiency component is disentangled from the composite term by means of the so called JLMS estimator (Jondrow et al., 1982):

$$E[u_{it}|\varepsilon_{it}] = \frac{\sigma\lambda}{1+\lambda^2}[\frac{\phi(\gamma_{it})}{1-\Phi(\gamma_{it})} - \gamma_{it}], \tag{1.12}$$

where $\sigma = \sqrt{\sigma_v^2 + \sigma_u^2}, \lambda = \frac{\sigma u}{\sigma v}$, $\gamma_{it} = \varepsilon_{it}\frac{\lambda}{\sigma}$. $\phi(\gamma_{it})$ and $\Phi(\gamma_{it})$ denote the standard normal density and the conditional density function evaluated at γ_{it}.

The TRE model is an extension of the pooled frontier model as it includes an additional firm-specific effect (δ_i) to capture any unobserved, constant characteristic of NHs that may affect their costs. It can be expressed as in 1.13:

$$\ln(\frac{C_{it}}{P_{m,it}}) = \delta_0 + \sum \delta_s \ln X_{s,it} + \delta_i + v_{it} + u_{it}, \qquad u_{it} \geqslant 0 \tag{1.13}$$

The effect δ_i is considered as a random effect. Albeit the model seems to have a three part disturbance term, in practice it is a usual random effect model in which the time-varying component $\varepsilon_{it} = v_{it} + u_{it}$ is asymmetrically distributed instead of normally (Greene, 2005):

$$f(\varepsilon_{it}) = \frac{\Phi(-\varepsilon_{it}\frac{\lambda}{\sigma})}{\Phi(0)}\frac{1}{\sigma}\phi(\frac{\varepsilon_{it}}{\sigma}) \tag{1.14}$$

It may be convenient to think of the TRE model as a random parameter model in which the intercept is the only random parameter. The number of parameters to estimate increases to N+K+2, which is not possible with the usual Maximum Likelihood Estimator (MLE). Greene (2001) proposed a direct maximization of the unconditional likelihood function by means of the Maximum Simulated Likelihood Estimator. When no closed form of the integral of the log-likelihood exists, this solution consists in maximizing the log-likelihood based on a simulated estimate of the density (Greene, 2012; Wooldridge, 2010). The conditional mean of the inefficiency term takes now the form $E[u_{it}|\delta_i + \varepsilon_{it}]$.

The adoption of the TRE model can be regarded as an improvement compared to the pooled frontier since the inclusion of firm-specific effects allows to control for the unobserved heterogeneity. However, if part of the inefficiency is constant over time, it is captured by the individual effects and, consequently, it is interpreted as heterogeneity rather than inefficiency. It follows that the overall inefficiency is underestimated and the term which is interpreted as inefficiency cannot capture the effect of the institutional form. This limitation is partially overcome by our second approach where gross inefficiencies include the impact of constant inefficiency due to the institutional form. Indeed, disentangling time-invariant inefficiency from latent heterogeneity is of major interest and may represent a valid improvement as compared to previous analysis of efficiency in NHs. Table 1.3 summarizes the econometric specification of the frontier models used in this study. For the reasons explained above, the TRE model represents our preferred model.

	Pooled model $half-normal$	TRE $half-normal$
Firm-specific effect δ_i	None	N (0, σ_δ^2)
Composite error ε_{it}	$\varepsilon_{it} = u_{it} + v_{it}$ $u_{it} \sim N^+(0,\ \sigma_u^2)$ $v_{it} \sim N(0,\ \sigma_v^2)$	$\varepsilon_{it} = u_{it} + v_{it}$ $u_{it} \sim N^+(0,\ \sigma_u^2)$ $v_{it} \sim N(0,\ \sigma_v^2)$

Table 1.3: Econometric specification of the pooled frontier and TRE models.

1.4.2 Panel-data models

The pooled OLS model assumes exogenous regressors and constant coefficients for both the intercept and the slopes. This estimator uses both the within (over time) and the between (across individuals) variation in the data and assumes that time effects are fixed and captured by the time variable included into the regressors (Cameron and Trivedi, 2010). In order to allow each firm to have a different intercept, the RE model is applied.

The individual-specific effects δ_i capture any unobserved, time-invariant heterogeneity. According to the model specification in (1.10), the RE model can be expressed as:

$$\ln(\frac{C_{it}}{P_{m,it}}) = \delta_0 + \sum \delta_s \ln X_{s,it} + v_{it} + \delta_i, \tag{1.15}$$

where X_s is again the vector of all explanatory variables s defined in 1.10. The unobservable individual effects are assumed to be random variables distributed independently of the regressors, that is: $\delta_i \sim (\delta, \sigma^2_{\delta_i})$ and the statistical noise $v_{it} \sim (0, \sigma^2_{v_i})$. The coefficients are estimated with Generalized Least Square (GLS) estimator. Consistent estimates of random effects models rely on the assumption of no correlation between the individual effects and the covariates. In this case, it means that the unobserved heterogeneity is uncorrelated with input choices and output. The null hypothesis of no correlation is rejected by the Hausman test (χ^2(21)=50.93, P-value=0.000). Estimates are likely to be affected by heterogeneity bias and therefore inconsistent. To assess the impact of this correlation, we also estimate regression models with the Mundlak correction (Mundlak, 1978; Wooldridge, 2010; Greene, 2012). The Mundlak specification considers this correlation explicitly in an auxiliary regression by including the mean of the covariates X in the specification of the cost function.

$$\delta_i = \sum \delta_s \overline{\ln X_{s,i}} + \alpha_i \qquad \overline{\ln X_{s,i}} = \frac{1}{T_i} \sum \ln X_{s,it}, \qquad \alpha_i \sim N(0, \sigma^2_\alpha) \tag{1.16}$$

In order to save degree of freedom in small sample, an ad-hoc Mundlak specification can be used where only the statistically significant means are considered (Hesketh and Skrondal, 2005). In the present case, a correlation is found with the regressors lnQ_1, $lnYQ_2L$, $lnYQ_1$, lnP_l and lnQ_1Q_2L. After including the mean of these variables in the cost model, the Hausman test cannot reject the null hypothesis of no correlation between individual effects and covariates (χ^2(18)=27.07, P-value=0.078). The results with the ad-hoc Mundlak correction are presented in Table 1.5 and show that our finding about the institutional form remain unchanged.

The fixed effects model provides an alternative estimator to tackle this issue as it allows for partial correlation between covariates and individual effects (Cameron and Trivedi, 2010). However, the fixed effects model does not allow to estimate the coefficient of time-invariant factors, such as the institutional form. For this reason, the fixed-effect estimator is excluded.

1.5 Results

We now discuss the results of the stochastic frontier approaches - with and without the institutional form dummy variable - estimated with a pooled frontier and a TRE model. In Table 1.4, we report the estimated coefficients together with their level of significance and, for Model 2 only, the impact of the dummy variable for the institutional form. Standard errors are given in brackets. All the first-order coefficients are highly significant and positive. The full list of estimates can be found in Appendix (Table 1.8). The estimated coefficients are quite robust across different specifications. Exceptions are the coefficients related to patients severity (δ_{Q_1}) and the lagged staff ratio (δ_{Q_2}). Both coefficients are lower when the individual effects are considered. This provides some evidence of unobserved heterogeneity, which is at least partially taken into account by the TRE estimation. In fact, the estimated coefficients are lower in the TRE estimation as compared to the coefficients of the pooled frontier.

The output coefficient (δ_Y) is slightly smaller than 1 and suggests the presence of unexploited economies of scale. The coefficients of the two output characteristics (δ_{Q_1}, δ_{Q_2}) show that more severe patients lead to higher costs. Similarly, more nurses per patient cause higher production costs. The estimated share of labor costs given by the coefficient of labor prices (δ_{P_l}) is between 63% and 70%, respectively in the TRE and the pooled models. The estimated share of capital costs is between 10% and 13%, whereas the proportion of material is between 18% and 25%.

The main variable of interest, the dummy for the institutional form in Model 2, is

Estimated coefficients	Stochastic frontier models (Model 1)		Stochastic frontier models with dummy variable (Model 2)	
	Pooled frontier	TRE	Pooled frontier	TRE
δ_Y	0.925***	0.929***	0.917***	0.926***
	(0.011)	(0.010)	(0.011)	(0.010)
δ_{Q_1}	0.313***	0.163***	0.313***	0.167***
	(0.043)	(0.034)	(0.044)	(0.033)
$\delta_{Q_{2L}}$	0.288***	0.190***	0.279***	0.189***
	(0.059)	(0.049)	(0.060)	(0.048)
δ_{P_l}	0.711***	0.630***	0.712***	0.623***
	(0.036)	(0.031)	(0.036)	(0.031)
δ_{P_k}	0.106***	0.128***	0.108***	0.128***
	(0.011)	(0.009)	(0.011)	(0.009)
δ_T	0.014***	0.013***	0.014***	0.013***
	(0.003)	(0.002)	(0.003)	(0.002)
δ_{IF}	-	-	0.011	0.010*
	-	-	(0.008)	(0.006)
$\lambda = \frac{\sigma_\mu}{\sigma_\nu}$	1.060***	1.744***	1.160***	1.846***
	(0.186)	(0.617)	(0.192)	(0.628)

Notes: Significance levels: * = 10%, ** = 5%, *** = 1%.

Table 1.4: Estimated first-order coefficients of pooled stochastic frontier models and TRE models (210 observations).

positive and only weakly significant at 10% level in the TRE model. Also, the magnitude of the coefficient is small. This provides weak evidence of performance differences between private-law NFP and public-law NHs.

In the last row of Table 1.4, we provide the statistics of the ratio between the standard deviation of the inefficiencies and the standard deviation of the stochastic term (λ). Since the value of λ defines the relative contribution of the inefficiency term with respect to the stochastic term, a positive and statistically significant number supports the existence of the two error components.[27] The difference in the lambda coefficient between the two models arises because of the different model specification.

The first-order parameters estimates of panel-data models, i.e. OLS, RE and RE with

[27] In addition, we performed an analysis of the skeweness of the OLS residuals. As Waldman (1982) shows, when the OLS residuals are skewed in the "wrong" direction, the results from the maximum likelihood estimator are those of a simple OLS rather than a cost frontier. The normality test shows that the OLS residuals are right skewed (0.23) and the null hypothesis of normally distributed residuals can be rejected at 99% significance level. Therefore, data and model specification support the adoption of stochastic frontier models.

Mundlak specification (RE_Mundlak), are presented as robustness check in Table 1.5. The full list of estimates is provided in the Appendix (Table 1.9). The results are very similar to the TRE model. We can see that when the correlation between individual effects and covariates is taken into account with the Mundlak formulation, the dummy remain statistically significant at the 10% level, showing some evidence of public-law NHs being more costly than private-law NHs by almost 2%.

Estimated coefficients	OLS	Std.Err.	RE	Std.Err.	RE_Mundlak	Std.Err.
δ_Y	0.917***	0.016	0.928***	0.015	0.919***	0.019
δ_{Q_1}	0.310***	0.071	0.193***	0.064	0.015	0.068
δ_{Q_2L}	0.280***	0.064	0.210***	0.064	0.196***	0.057
δ_{P_l}	0.711***	0.042	0.640***	0.037	0.635***	0.048
δ_{Pk}	0.108***	0.014	0.124***	0.013	0.116***	0.014
δ_T	0.014***	0.003	0.013***	0.002	0.014***	0.002
δ_{IF}	0.009	0.011	0.006	0.013	0.019*	0.011
δ_0	15.449***	0.014	15.446***	0.014	15.434***	0.013
R^2	0.983		0.987		0.988	

Notes: Significance levels: * = 10%, ** = 5%, *** = 1%.

Table 1.5: Results of the non-frontier models OLS, RE and RE_Mundlak (210 observations).

Descriptive statistics of the estimated inefficiency levels are shown in Table 1.6, separately for public-law and private-law NFP NHs. Two interesting aspects are worth noting. First, estimated inefficiencies in the pooled and the TRE effect model reach very similar values, indicating a low impact of unobserved heterogeneity on the estimated inefficiencies. Second, the level of inefficiency of public-law and private-law NFP NHs is also equivalent. The inefficiency level of NHs ranges between 1% and 9.4%, with an average value of 3.3%.

	Mean	Std.Dev.	Min	Max
Private-law NFP NHs				
Pooled	0.0348	0.0150	0.011	0.094
TRE	0.0328	0.0155	0.010	0.080
Public-law NHs				
Pooled	0.0344	0.0122	0.012	0.068
TRE	0.0320	0.0139	0.009	0.079

Table 1.6: Mean inefficiency levels by institutional form and model.

The Kruskal-Wallis test on the null hypothesis of equal inefficiency mean between the two institutional forms (Table 1.7) confirms our expectations. In the first two columns of Table 1.7 we report the results of the test for Model 1, where we do not control for the institutional form in the main cost equation. P-values are reported in brackets. The test does not reject the null hypothesis of equal mean inefficiency between public-law and private-law NFP NHs in both model specifications (pooled and TRE). The results of the pooled frontier model may suffer from heterogeneity bias, while in the TRE model constant inefficiency may be captured by the individual effects. In the remaining columns of Table 1.7 we report the results of the Kruskal-Wallis test for Model 2, with inefficiency net of the institutional form effect. The Kruskal-Wallis test suggests that time-varying inefficiency does not differ significantly across institutional forms either.[28]

Kruskal-Wallis test	Inefficiencies (Model 1)		Net inefficiencies (Model 2)	
	Pooled	TRE	Pooled	TRE
Public-law=Private-law	NO	NO	NO	NO
(P-value)	(0.178)	(0.895)	(0.729)	(0.148)

Table 1.7: Results of the Kruskal-Wallis test on the equality of mean inefficiency between public-law and private-law NHs.

1.6 Conclusions

Do public-law NHs differ from private-law NFP NHs? To tackle this question we developed a model of cost efficiency in NHs where firms are local monopolies financed by the regional government through an ex-ante budget. Cost efficiency depends on the institutional form because of different legal constraints faced by the management in the decision-making process and the degree to which the management internalizes the objectives of the board. Our model hypothesized that, under certain conditions, private-law NFP institutions may be more efficient than public NHs.

[28] We also estimate a model where we replaced the dummy for the institutional form with a dummy for the ownership form. The results show that ownership form (private/public) does not affect total costs.

Differences within the nonprofit NH industry are investigated based on data from Swiss-Italian NHs. The presence of latent heterogeneity, due for instance to inaccurate measures of patients severity of illness, suggested that the TRE model may avoid biased estimates. However, this model suffers from the limitation of interpreting persistent inefficiency as latent heterogeneity. To address this issue, we included a dummy variable for the institutional form in the deterministic part of the frontier. The skewed term instead allowed for time-varying inefficiency. We believe that the approach proposed may provide a valuable strategy to assess the impact of organizational characteristics on the performance of firms in the presence of unobserved heterogeneity.

Our empirical analysis did not show strong evidence of differences between public-law and private-law NFP NHs. Therefore, these findings partially differ from previous analyses performed on Swiss NHs, which generally report higher efficiency levels for private-law NFP NHs. Our proposed strategy may better disentangle constant inefficiency from unobserved heterogeneity. Moreover, differences may also result from an improved specification of the cost function, regarding the price of capital, and refined data on capital costs for public-law NHs.

One possible explanation of these results lays in the extensive regulation that affects all institutional forms in Switzerland. Since costs are tightly controlled by the regulator, little room is left for management discretion. Other explanations may be that NHs are generally overfinanced or that private-law NFP NHs face similar constraints as public-law NHs. Foundation councils may put curbs on the decision power of their managers, as in public-law NHs.

From a policy point of view, no evidence of differences across institutional forms in the NH sector may advise that regulation can be successful in driving different institutional forms towards more homogeneous performances.

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Appendix

Estimated coefficients	Stochastic frontier models with dummy variable (Model 2)			
	Pooled Frontier	Std.Err.	TRE	Std.Err
δ_Y	0.917***	0.011	0.926***	0.010
δ_{Q_1}	0.313***	0.044	0.167***	0.033
δ_{Q_2L}	0.279***	0.060	0.189***	0.048
δ_{P_l}	0.712***	0.036	0.633***	0.031
δ_{Pk}	0.108***	0.011	0.128***	0.009
δ_T	0.014***	0.003	0.013***	0.002
δ_{YY}	-0.008	0.037	0.022	0.029
$\delta_{Q_1Q_1}$	1.316***	0.504	1.053**	0.417
$\delta_{Q_2LQ_2L}$	0.105	0.355	-0.030	0.349
$\delta_{P_lP_l}$	-0.130	0.273	0.407*	0.231
$\delta_{P_kP_k}$	0.124***	0.028	0.157***	0.022
$\delta_{Q_1Q_2L}$	-0.496	0.303	-0.197	0.269
δ_{YQ_2L}	0.217*	0.130	0.019	0.111
δ_{YQ_1}	-0.054	0.101	-0.260***	0.091
δ_{YP_l}	0.141*	0.074	0.159**	0.068
δ_{YP_k}	0.021	0.020	0.028*	0.016
$\delta_{Q_1P_l}$	0.509**	0.258	0.515**	0.221
δ_{Q_1Pk}	-0.305***	0.089	-0.256***	0.08
$\delta_{P_lQ_2L}$	-0.461*	0.247	-0.372	0.247
δ_{PkQ_2L}	-0.117	0.088	-0.052	0.081
$\delta_{P_kP_l}$	-0.065	0.077	-0.157**	0.061
δ_{IF}	0.011	0.008	0.010*	0.006
δ_0	15.410***	0.013	15.409***	0.010
$\lambda = \frac{\sigma_\mu}{\sigma_\nu}$	1.161***	0.192	1.846***	0.628

Notes: Significance levels: * = 10%, ** = 5%, *** = 1%.

Table 1.8: Full stochastic frontier models estimates of Model 2 (210 observations).

Estimated coefficients	OLS	Std.Err.	RE	Std.Err.	RE Mundlak	Std.Err.
δ_Y	0.917***	0.016	0.928***	0.015	0.919***	0.019
δ_{Q_1}	0.310***	0.071	0.193***	0.064	0.015	0.068
δ_{Q_2L}	0.280***	0.064	0.210***	0.064	0.196***	0.057
δ_{P_l}	0.711***	0.042	0.640***	0.037	0.635***	0.048
δ_{Pk}	0.108***	0.014	0.124***	0.013	0.116***	0.014
δ_T	0.014***	0.003	0.013***	0.002	0.014***	0.002
δ_{YY}	-0.011	0.044	-0.013	0.049	0.019	0.052
$\delta_{Q_1Q_1}$	1.364	0.840	1.196	0.765	1.236**	0.755
$\delta_{Q_2LQ_2L}$	0.078	0.513	-0.073	0.450	-0.058	0.413
$\delta_{P_lP_l}$	-0.111	0.362	0.353	0.264	0.510*	0.308
$\delta_{P_kP_k}$	0.122***	0.027	0.155***	0.025	0.156***	0.030
$\delta_{Q_1Q_2L}$	-0.632	0.430	-0.335	0.364	-0.040	0.310
δ_{YQ_2L}	0.216	0.152	0.061	0.130	-0.000	0.126
δ_{YQ_1}	-0.044	0.118	-0.228**	0.099	-0.571***	0.121
δ_{YP_l}	0.127	0.081	0.163**	0.066	0.118	0.082
δ_{YP_k}	0.021	0.021	0.029	0.021	0.049*	0.026
$\delta_{Q_1P_l}$	0.522*	0.288	0.627**	0.243	0.544*	0.292
δ_{Q_1Pk}	-0.297***	0.080	-0.277***	0.079	-0.251***	0.102
$\delta_{P_lQ_2L}$	-0.502*	0.283	-0.364	0.243	-0.326	0.227
δ_{PkQ_2L}	-0.130	0.096	-0.063	0.075	-0.012	0.093
$\delta_{P_kP_l}$	-0.059	0.083	-0.154**	0.070	-0.201***	0.088
δ_{IF}	0.009	0.011	0.006	0.013	0.019*	0.011
δ_0	15.449***	0.014	15.446***	0.014	15.434***	0.013
R^2	0.983		0.987		0.988	

Notes: Significance levels: * = 10%, ** = 5%, *** = 1%.

Table 1.9: Results of the non-frontier models OLS, RE and RE Mundlak (210 observations).

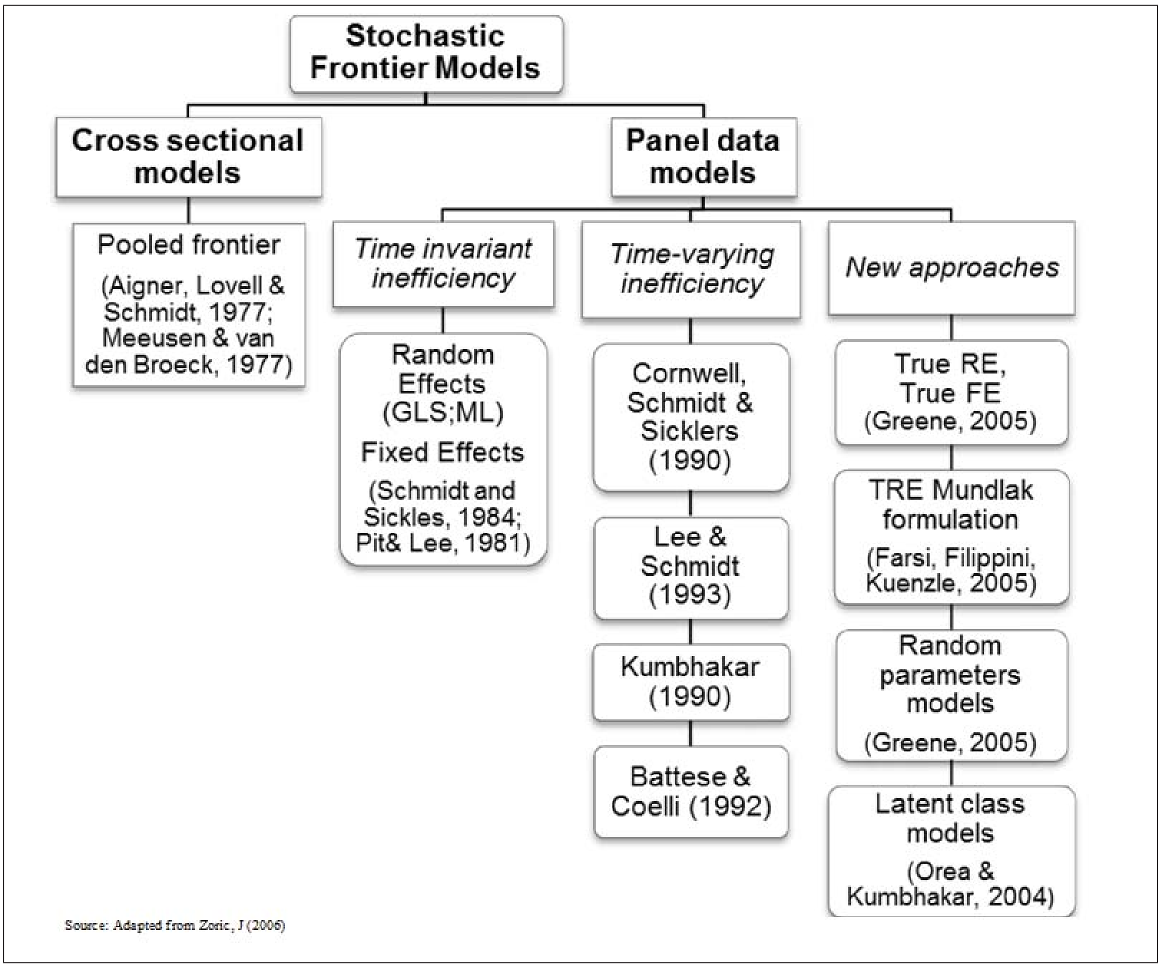

Figure 1·1: Overview of Stochastic Frontier Models.

Chapter 2

Implications of global budget payment system on nursing home costs

2.1 Introduction

Increasing health care expenditures for the elderly population is a major concern for society and policymakers. In Europe, the percentage of people over 64 rose rapidly in the past decades and is expected to increase between two and six times by 2060, ranging from 22-25% in Belgium, Denmark, Ireland, and the United Kingdom, to 33-36% in Bulgaria, Germany, Latvia, Poland, Romania, and Slovakia. The share of very elderly people (80 and over) in the EU15 experienced the highest increase among all age classes, from 1.2% in 1950 to 4.2% in 2010, and is projected to almost triple (12%) by 2060 in the EU27 (Eurostat, 2012; European Union, 2012). Accordingly, the demand of nursing home care is expected to increase rapidly raising the burden on public resources generally used to cover nursing home costs or to subsidize prices of nursing home services (Karlsson et al., 2006).

In the past 30 years hopes have been pinned on the possibility to control healthcare expenditures by replacing Retrospective (RPS) with Prospective Payment Systems (PPS), mainly in the hospital sector. Under PPS, a predetermined, fixed amount of resources is paid for the service. The rationale is that reimbursement based on ex-ante costs prevents health care providers from giving unnecessary care (Jegers et al., 2002). In the U.S., the use of PPS has been extended from hospitals to the nursing home sector in 1997 through the Balanced Budget Act. Similarly, many European countries have recently incorporated more incentivizing payment systems into their existing funding systems.

Although the health economics literature is rich of studies on the impact of PPS in the U.S. nursing home sector (e.g. Chen and Shea, 2002; Norton, 1992; Zhang et al., 2008), there is little empirical evidence in Europe. A number of studies have been published on the impact of PPS in the hospital sector in different European countries, for instance Finland (Linna, 2000), Norway (Biorn et al., 2006), and Portugal (Dismuke and Sena, 1999). To our knowledge, the only study on the impact of PPS to finance nursing home services is the recent analysis by Dormont and Martin (2012) based on a hypothetical scenario. The authors investigate the costs-efficiency trade-off in French nursing homes (NHs) to predict possible implications of a switch in the payment system.

In this study, we provide evidence on the impact of PPS on the costs of a sample of NHs operating in one Swiss region (canton Ticino) by exploiting data before and after the introduction of PPS. Switzerland is a federal state in which the provision and regulation of nursing home care for elderly people is organized at the regional level (cantons). As consequence, institutional and organizational aspects of nursing home care vary across the 26 cantons. In 2006, the cantonal authority in the Italian-speaking region of Switzerland (Ticino) substituted the previously-in-force payment system based on acknowledged financial needs (RPS) with an ex-ante determined budget (PPS). To evaluate the impact of this policy change we use i) an econometric model with fixed-effects (FE) and a time trend that is allowed to change after the policy reform and ii) a counterfactual approach (CF) consisting in estimating a fixed-effects model to predict costs for the years after the reform and calculating the impact of the reform as the difference between observed- and predicted costs in each year. We will provide evidence that the new payment system reduced costs growth for NH care, after controlling for the quality of services.

The remainder of the chapter is organized as follows. Section 2.2 provides an overview of recent studies analyzing the impact of PPS on costs, quality and access to health care services. Section 2.3 describes the regulatory reform and proposes a simple theoretical model to infer the behavior of NHs under the old RPS and the new PPS. Data and identification strategy for the policy change are discussed in section 2.4. The econometric estimations are presented in section 2.5, and section 2.6 concludes the chapter.

2.2 Previous research on the impact of PPS in nursing home care

The empirical evidence regarding the impact of PPS on costs, quality and access in NHs care is not conclusive. The literature mostly relies on studies conducted during the 90s in the U.S. where PPS were firstly introduced. Some of these studies focus on the financial consequences of PPS by looking at changes in costs (e.g. Ohsfeldt et al., 1991; Sexton et al., 1989). More recently, attention has been devoted to the understanding of cost reduction achievements. Improved methods to control for changes in quality and to cope with the potential endogeneity of output and/or quality in cost functions have been proposed (Gertler and Waldman, 1992; Chen and Shea, 2002). Also, direct assessment of the impact of PPS on quality (Konetzka et al., 2004; Konetzka et al., 2006) and access to nursing care (Coburn et al., 1993) have been carried out.

Regarding the effects on costs, Sexton et al. (1989) use a two steps strategy to regress efficiency scores calculated using Data Envelopment Analysis (DEA) on changes in the payment system occurred in the State of Maine in 1982. They find a decrease in technical efficiency. Quality variations are assumed to be negligible. Ohsfeldt et al. (1991) exploit variations in the payment systems of 47 U.S. states over a 12-years period using a random effects model. After correcting for endogeneity in the reimbursement system by means of instrumental variables, the authors find a reduction of 20 per cent in per diem costs due to PPS.

Coburn et al. (1993) extend the traditional cost analysis by looking at the consequences of PPS on quality and access for Medicaid patients in the State of Maine. The analysis shows that PPS reduces growth in per-patient variable costs. During the first three years after the introduction of PPS, the average savings and losses per patient day decreased substantially. Afterward, the authors observed a remarkable increase in the number of NHs experiencing losses. Only the percentage of room and board costs relative to the total variable costs decreased over time, suggesting that cost savings were not achieved through reductions in quality. Finally, the percentage of Medicaid patients decreased, which can be interpreted as a negative impact on access for most severe patients.

Concerns about the evidence obtained during the 90s are raised by Chen and Shea (2002), who question the methodology used. In particular, they point at the inadequate measures of quality and output/quality endogeneity in cost functions. To cope with the endogeneity issue, the authors construct instrumental variables for both output and quality, and investigate the impact of PPS on short-term operating costs. The analysis is performed on a one-year data set of different U.S. states grouped into three different payment systems. The authors show that NHs with PPS are no longer significantly cheaper than facilities subject to cost-based retrospective payments, after controlling for quality differences.

More recently Zhang et al. (2008) assess the impact of PPS on the cost efficiency of 8361 NHs in the U.S. over the period 1997-2003. During this period, three major policy changes occurred. In 1997, the Balance Budget Act (BBA) ratified the introduction of PPS. Afterward, the Balanced Budget Refinement Act (BBRA, 2000) and the Benefit Improvement and Protection Act (BIPA, 2001) increased the baseline payments in consequence of the financial difficulties reported by NHs. DEA calculated efficiency scores are regressed on policy change variables identified with time markers and a truncated random effect model is applied. The results show a negative relationship of all policy change variables with efficiency scores. The authors capture quality differences by weighting the output with a score calculated using the number of deficiency citations.

A growing strand of literature investigates the impact of PPS on quality aspects of NH care. Using data on U.S. NHs over the period 1996-2000, Konetzka et al. (2004) study the impact of PPS on quality by applying a difference-in-difference approach and a negative binomial model. The authors use changes in the professional staffing and the number of regulatory deficiencies as proxies for quality. As expected, PPS is found to significantly reduce the professional staff. The negative impact of PPS is partially corrected by the introduction of the Balanced Budget Refinement Act. As with respect to regulatory deficiencies, only weak evidence is reported. Also, no differences between for-profit and nonprofit NHs are found.

Finally, Konetzka et al. (2006) investigate the spillover effects of introducing PPS in Medicare residents on quality for Medicaid patients. Since facilities cross-subsidize part of the costs of Medicaid residents with the higher margins of Medicare and high private-pay residents, the cuts in revenue due to the introduction of PPS may also have affected quality of long-stay residents. Using a quasi-experimental approach in four U.S. states over the period 1995-2000, the authors show that PPS has an adverse effect on urinary tract infections and pressure sores.

To conclude, the literature remains inconclusive as with respect to the impact of PPS in nursing home care. Also, it is worth pointing out that most of the studies mentioned are conducted in the U.S. where private for-profit facilities represent a large share of total NHs and the environment is increasingly competitive. It is not clear whether this leads to different behavioral responses as compared to nonprofit institutions, which are largely present in Europe. In competitive environments, the expected negative impact of cost reductions on quality may be mitigated by the need to maintain a high reputation. As suggested by Grabowski and Town (2011), NHs facing greater competition are more responsive to quality improving projects. However, competition can also have a negative effect on quality if it pushes prices down (Forder and Allan, 2012). Conversely, in a non-competitive, nonprofit environment with highly regulated prices and quality, such as the Swiss NH sector, the possible negative impact of cost reductions on quality is expected to be limited.

2.3 The regulatory reform

2.3.1 Background

In Ticino, NH care is provided primarily by regulated public and private nonprofit organizations. The provision of nursing care is further decentralized at local level (municipalities) and elderly people are commonly assigned to the NH in the community of residence. Therefore, NHs operate as local monopolies with virtually no competition. Price and quality are regulated by the cantonal authority, i.e. the Regional Department of Public Health (RDPH). Prices are subsidized and defined by the RDPH as a function of residents' income (pension payments) and wealth, and do not vary across NHs. Quality is regulated in many structural and procedural aspects. Because of tight regulation the production process is highly homogeneous.

In 2006, the cantonal authority in Ticino introduced global budgets for NH care. Prior to the introduction of global budgets, subsidies to providers of long term care were allocated by the cantonal authority based on acknowledged financial needs, i.e. a form of soft budget constraint. The payment system consisted of two parts: a prospectively defined component and a retrospective, upward adjustment based on actual costs at the end of the year. The prospective part was an estimation of the costs for the following operative year based on a combination of historical costs and benchmarking parameters at the sector level. At the end of the year, more financial resources were paid if the NH was able to justify additional expenses. Conversely, service providers with year-end costs below the initially estimated financial need were not allowed to retain the "savings". The cantonal authority viewed this system as inflationary and poorly incentivizing. The low flexibility of the system due to the detailed control over all cost items made it almost impossible for the management to make decisions on the cost structure, and led to low responsibility as with respect to budget decisions and financial performance. The funding system had the adverse incentive to spend the whole amount of resources provided.

In the early 2000s, to respond to the need of improving transparency and efficiency in long term care, the RDPH modified the payment system. To develop a new funding system based on prospectively defined payment rates, a pilot phase was launched in January 2003. Five NHs were selected to participate in the pilot phase over a three-years period. Information collected during these years were used to define the list of services provided, an analytical accounting system, and a package of modern managerial tools. Since January 2006, the system has been applied to all NHs.

The current payment system (global budget) is composed of two elements: an individual component and a standardized part. The individual component mainly covers fixed costs such as rents and expenses for education trainings. The standard component includes four main categories of costs: residential, animation, care and therapies. Global budgets are calculated by multiplying standard prices (also called *prospective rates* in the literature) with quantities. Standard prices stem from the analytical accounting register and reflect median costs in the nursing home industry classified into nine categories according to size. Also, standard prices are calculated to implicitly define the level of efficiency and quality desired by the cantonal authority. Quantities are given by the number of beds times the level of occupancy and yearly-days. For nursing care services, the number of resident-days is weighted by the NH-specific case-mix index calculated by the RDPH.

The starting prospective rate was determined for the year 2005, while the prospective payment rates for the following years were adjusted for inflationary changes of some cost items only (e.g. wages). An adjustment based on savings achieved in the previous years is planned to occur on a medium-term perspective depending on the financial stability of the NHs and has not been applied yet.

The final budget does not depend on the actual costs generated by the residents. NHs with end-year costs lower than the global budget are entitled to retain a share (25%) of the savings. The main part (75%) are saved as mandatory reserves to cover previous or future deficits. This system is expected to ensure financial stability of nursing care providers in the medium-term.

A possible consequence of the new payment system is the negative impact on quality levels of NH services. This risk may even be higher with excess of demand since incentives to compete are lower. Nevertheless, this effect if unlikely given the existing regulation of structural and procedural aspects of the production and provision of NH care. For instance, the RDPH defines the number of care givers in each NH as well as their skill levels. Also, a new managerial system for quality promotion and control has been adopted.

2.3.2 A simple model

Before assessing the impact of the new payment system empirically, we sketch a simple theoretical model to illustrate differences in the behavior of NHs under the old and the new payment schemes, respectively the soft budget constraint (RPS) and the prospective payment (PPS) introduced recently. The demand of NH care is independent of prices because fees are established by the RDPH and are homogenous across the canton. Moreover, similarly to Chalkley and Malcomson (1998), the demand of NH care does not reflect quality.[1] We define NH total costs as:[2]

$$C = \widetilde{\theta} - e \tag{2.1}$$

where $\widetilde{\theta} \epsilon \left[\overline{\theta}, \underline{\theta}\right]$ is an exogenous cost component with $\overline{\theta} > \underline{\theta}$ and probability distribution $\Pr(\theta = \underline{\theta}) = q$ and $\Pr(\theta = \overline{\theta}) = 1 - q$, and only partially observable by the regulator.[3] The last term (e) in the equation (2.1) is cost-reducing effort. We normalize the population of patients to one, so that eq. (2.1) is also the average cost function. The prospective budget is a function $P(\theta, q)$ of costs the NH is expected to incur during the operating year:

$$P(\theta, q) = q\underline{\theta} + (1 - q)\overline{\theta}. \tag{2.2}$$

[1] There are two main arguments in support of this assumption. First, patients may not be able to assess the multidimensional nature of quality. Second, quality is partially an experience good and is observable only after receiving care. These aspects are particularly relevant in the case of nursing care due to the type of patients and the nature of the service. Also, in the Swiss context, individuals do not have free choice of the NHs and the allocation occurs according to the place of residence. Finally, the regulator sets quality standards, which results in highly homogeneous nursing home services.

[2] A similar frame is adopted in chapter 1 of the thesis to investigate cost efficiency in public-law and private-law nonprofit NHs. However, the authors focus on differences in managerial behavior due to the institutional form rather than changes in the payment scheme.

[3] This reflects, for instance, the number of days spent by NH residents. While the number of residents per year is known in advance due to an excess of demand, uncertainty remains about the type and intensity of care needed by residents. Also, uncertainty is related to structural costs for standard daily activities, such as eating and other physical activities, or costs related to the geographical location of the NH.

The NH maximizes the following objective function:

$$U = W - \lambda_i^{\theta}(B - C)^2 - \phi(e) \tag{2.3}$$

where W represents exogenous benefits from the production of NH services, and $\lambda_i^{\theta} \epsilon (\lambda_i^{\underline{\theta}}, \lambda^{\overline{\theta}})$ captures the marginal impact of an unbalanced budget from the i^{th} payment scheme ($i \ \epsilon \ [RPS, PPS]$) where:

$$\lambda_{PPS}^{\underline{\theta}} = \lambda^{\overline{\theta}}(\alpha - 1) \qquad\qquad 0 < \alpha \leq 1,\ \lambda^{\overline{\theta}} > 0 \tag{2.4}$$

and

$$\lambda_{RPS}^{\underline{\theta}} = -\lambda_{PPS}^{\underline{\theta}}. \tag{2.5}$$

Note that two scenarios are possible: over financing ($\theta = \underline{\theta}$) and under financing $\left(\theta = \overline{\theta}\right)$. Remember that the budget is defined by the RDPH as a weighted average of the structural cost parameter (eq. 2.2). Using (2.1) and (2.2), we then observe that for $\theta = \underline{\theta}$ we have $B - C > 0$ for any level of effort e. Conversely, for $\theta = \overline{\theta}$, we have $B - C \leq 0$ for any $e \in [0, e_{bal}]$.[4] Consequently, eq. (2.3) assumes that underfinancing reduces NH utility under both payment regimes, RPS and PPS, since$\lambda^{\overline{\theta}} > 0$. Conversely, incentives for the two regimes differ in the case of overfinancing since $\lambda_{RPS}^{\underline{\theta}} \neq \lambda_{PPS}^{\underline{\theta}}$. Under the old payment regime (RPS), NHs were not allowed to retain resources in excess at the end of the year. Substituting (2.4) into (2.5) and then (2.5) into the utility function defined by (2.3), we see that profits decrease. Moreover, the marginal impact of profits is generally lower than the marginal impact of losses ($\alpha - 1 \leq 1$). Under the new PPS system, NHs are entitled to retain resources in excess. Since $\lambda_{RPS}^{\underline{\theta}} = -\lambda_{PPS}^{\underline{\theta}}$, we allow surpluses to increase utility under the PPS regime only. Finally, $\phi(e)$ is the disutility of effort to reduce costs, which is increasing in the level of effort, with $d\phi/de > 0$ and $d^2\phi/de^2 > 0$. We specify the disutility of effort as $\phi(e) = \frac{\eta}{2}e^2$, with $\eta > 2\lambda^{\overline{\theta}}$. The marginal impact of effort on NH's utility is then

[4] Note that the equilibrium level of effort for $\theta = \overline{\theta}$ is always lower that e_{bal}. See Table 2.1 for details.

captured by the parameter η.

To calculate the optimal level of effort, we first substitute (2.1), (2.2) and $\phi(e)$ into (2.3) and derive the following first-order condition:

$$\frac{dU}{de} = -2\lambda_i^{\theta}\left[(\overline{\theta} - \widetilde{\theta}) - q(\overline{\theta} - \underline{\theta}) + e^*\right] - \eta e^* = 0. \tag{2.6}$$

We then solve (2.6) for the equilibrium level of effort under the two financing regimes (RPS and PPS) and scenarios (underfinancing and overfinancing). The results are summarized in Table 2.1 where $\beta = 2\lambda^{\overline{\theta}}$ for simplicity.

	RPS	PPS
$\theta = \overline{\theta}$	$e_{SBC}^{\overline{\theta}*} = \frac{\beta q(\overline{\theta}-\underline{\theta})}{\eta+\beta}$	$e_{PPS}^{\overline{\theta}*} = \frac{\beta q(\overline{\theta}-\underline{\theta})}{\eta+\beta}$
$\theta = \underline{\theta}$	$e_{SBC}^{\underline{\theta}*} = 0$	$e_{PPS}^{\underline{\theta}*} = \frac{\beta(1-\alpha)(1-q)(\overline{\theta}-\underline{\theta})}{\eta-\beta(1-\alpha)}$

Table 2.1: Equilibrium level of cost reducing efforts under different payment systems and structural costs.

As expected, no differences in incentives arise between the two regimes in the case of underfinancing ($\theta = \overline{\theta}$). However, the new regime (PPS) provides more incentives to cost containment in the case of overfinancing if $\alpha < 1$ and $\beta > 0$. Therefore, the ability of the new payment system to control costs is related to the importance that NHs attach to additional resources, which is captured by $\beta\,(\alpha - 1)/2$ or $\lambda^{\overline{\theta}}\,(\alpha - 1)$ as defined by (2.4). This weight may be relatively weak since NHs operating in our context are generally nonprofit firms. One last consideration arises from the impact of the parameter η. Since NHs are nonprofit firms, η may represent not only the marginal cost of effort to reorganize the production process and save costs but also the disutility caused by reducing working time per employee or the number of employees. If those costs are very high (e.g. $\eta \to \infty$), then cost reducing effort tends to zero under both regimes, and incentives are invariant.

2.4 Empirical specification

2.4.1 The cost function

To empirically investigate the impact of global budget payments in NH care, we exploit data from a natural experiment in Switzerland where the payment system recently changed from RPS to PPS. Similarly to Farsi et al. (2008), we assume that NHs transform two inputs, capital and labor, into a single output, measured by the number of patient-days of nursing home care.[5] Since the production process is highly homogenous among NHs, the number of resident-days can represent a good indicator of the level of production. Consequently, we specify a total costs function which depends on output (Y), price of capital and labor (P_k and P_l), two output characteristics (Q_1 and Q_2), and a general time trend (τ).[6,7]

$$C = f(Y, P_k, P_l, Q_1, Q_2, \tau). \tag{2.7}$$

The price of labor is calculated as the weighted average wage of different professional categories employed in the NH (doctors, nurses, administrative and technical staff), while the price of capital is derived from the residual approach, i.e. labor costs are subtracted from total costs and the residual is divided by the capital stock approximated by the number of beds. Q_1 is an index which measures the average patients' assistance need by means of normal daily activities such as eating, personal care or physiological activities. This is calculated on a yearly basis by the cantonal authority. Patients are classified in one out of five categories according to their severity level. A value between 0 and 4 is assigned

[5] The specification of the cost function in this chapter differs from the specification in chapters 1 and 3, where three input prices are included. The inclusion of the third input became possible only recently due to new, more detailed data received.

[6] In a non-competitive environment such as the Swiss one, there is no reason to assume that NHs minimize costs. In this case, the cost function is a *behavioral cost function* (Evans, 1971) and can still be used to make a comparison among firms. Moreover, by estimating a total cost function instead of a variable cost function we avoid the risk related to a high correlation between capital stock and output, which leads to a positive relationship between variable costs and capital stock. A similar approach is used, for instance, by Farsi and Filippini (2004).

[7] In order to estimate a cost function, either the output is assumed to be homogenous or we need to control for service intensity and patients' characteristics (Birnbaum et al., 1981).

where higher values indicate more severe cases. Q_2 is the nursing staff ratio, that is the ratio between the number of nurses employed in a NH and the optimal number of nurses that should be employed according to the guidelines of the cantonal authority.

Because NH care is a labor-intensive service, the nursing staff ratio can be considered as a good indicator of quality (see for example Johnson-Pawlson and Infeld, 1996; Schnelle et al., 2004). Labor costs represent the main costs of a NH and make about 80 per cent of total costs. Consequently, a small change in the nursing staff ratio may affect total costs considerably. The nursing staff ratio is, therefore, a key variable in our analysis since NHs with relatively high costs may decide to decrease the number or quality of workers to save money. If this is the case, then the estimates could suffer from endogeneity bias. To test the endogeneity of this regressor, we perform the robust Durbin-Wu-Hausman test.[8]

In order to impose as few restrictions as possible to (2.7), we adopt a flexible translog functional form approximated at the median value. Input prices and total costs are divided by the price of capital in order to satisfy the homogeneity condition in input prices.[9] The translog approximation to (2.7) can be written as:

$$\begin{aligned}
\ln\left(\frac{C}{P_k}\right) \quad = \quad & \delta_0 + \delta_Y \ln Y + \delta_{Q_1} \ln Q_1 + \delta_{Q_2} \ln Q_2 + \delta_{P_l} \ln \frac{P_l}{P_k} \\
& + \frac{1}{2}\delta_{YY}(\ln Y)^2 + \frac{1}{2}\delta_{Q_1Q_1}(\ln Q_1)^2 + \frac{1}{2}\delta_{Q_2Q_2}(\ln Q_2)^2 \\
& + \frac{1}{2}\delta_{P_lP_l}\left(\ln \frac{P_l}{P_k}\right)^2 + \delta_{YQ_1} \ln Y \ln Q_1 + \delta_{YQ_2} \ln Y \ln Q_2 \\
& + \delta_{YP_l} \ln Y \ln \frac{P_l}{P_k} + \delta_{Q_1P_l} \ln Q_1 \ln \frac{P_l}{P_k} + \delta_{Q_1Q_2} \ln Q_1 \ln Q_2 \\
& + \delta_{P_lQ_2} \ln \frac{P_l}{P_k} \ln Q_2 + \delta_t \tau + \varepsilon \qquad (2.8)
\end{aligned}$$

where ε is the error term which may contain individual effects δ_i. The individual subscript

[8] The test is robust to arbitrarily violations of conditional homoskedasticity and clustering, and consists in estimating the model by a Generalized Method of Moments (GMM) estimator and applying the Sargan statistic. We perform this test using the lagged value of Q_2 as an instrumental variable. The test statistic is χ^2 distributed with a robust score $\chi^2(1) = 0.49$ or $F(1, 234) = 0.395$. The null hypothesis of exogenous Q_2 cannot be rejected at any standard level of significance.

[9] The cost function is linear homogenous of degree 1 in input prices when a 10% increase in all input prices leads to a 10% increase in total costs.

i and the time subscript t are omitted for simplicity. We check for the concavity condition in input prices after the estimation.

2.4.2 Data and descriptive statistics

Our study builds on data extracted from annual reports delivered to the cantonal authority by all regulated NHs scattered in canton Ticino, Switzerland. The initial data set contains 50 NHs observed over a 10-years period (2001-2010). This period includes the 5-year period before and the 5-year period after implementation of global budgets. From this initial sample, we exclude 5 NHs either because a considerable share of the output (patient-days) is produced in foyers[10] or they show unreasonable values for some variables of interest and are therefore dropped.[11] Finally, we exclude the NHs selected for the pilot phase of global budget adoption for three main reasons. First, the pilot phase was mainly intended to set down the rules of the new payment system and to understand its functioning. The new payment system was introduced stepwise and adjusted over time. Second, pilot NHs are few and are observed for a too short period (3 years) to be used as control group. Finally, these NHs were not randomly selected.[12]

The final sample consists of an unbalanced panel of 41 NHs observed for 10 years (400 observations). The minimum number of observations per cluster is 7, while on average information are available over the whole period (9.75 years). In Table 2.2 we report some descriptive statistics of the characteristics of NHs, which include the mean, the standard deviation, and the first and third quartiles.

On average, NHs have 67 beds and provides services for 23734 resident days yearly, each of which costs about SFr. 248. The nursing staff ratio is 0.95 indicating that, on

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[10] Foyers are external residential apartments where the healthiest patients get nursing care. Therefore, the production process of these NHs might differ a lot as compared to the others.

[11] These are private for-profit institutions that have been placed under the cantonal authority and largely subsidized. This implied a change in the production process and hardly comparable data.

[12] In Table 2.6 (cfr. Appendix) we show that pilot NHs are relatively cheaper than non-pilot NHs. Also, in Table 2.7 (cfr. Appendix) we show that the cost evolution over time differs between the two groups: pilot NHs experience a more important cost increase before the pilot phase, while from the extended introduction of the new payment system their costs increase relatively less than non-pilot NHs.

Variables	Description	Mean	Std. Dev.	1^{st} q.	3^{rd} q.
AC	Average cost per resident day	247.65	23.43	232.20	262.50
Y	Total resident days per year	23734	8532	17595	27768
Q_1	Average dependency index	3.13	0.35	2.9	3.4
Q_2	Nursing staff ratio	0.95	0.08	0.9	0.98
P_l	Average labor price per employee per year	82051	4525	79456	85091
P_k	Average capital price per bed	16233	3141	14360	17788
K	Number of beds	67	24	50	80

Notes: All monetary values are in 2005 Swiss francs (SFr.) adjusted by the national Consumer Price Index.

Table 2.2: Descriptive statistics of costs, inputs and output characteristics over the whole period.

average, the personnel employed by NHs is close to the amount suggested by the cantonal authority. The average price of labor is about SFr. 82051 per year, while the price of capital is SFr. 16233 per bed.

A considerable variation is observed across NHs in almost all variables. The average cost per resident day of the first quartile is around SFr. 232, and increases to SFr. 262 in the third quartile. The size of NHs also varies remarkably: three-quarters of NHs provide less than 80 beds, and the biggest NH has 145 beds. This sizable variation can be read also in the number of resident days.

As with respect to input prices, we can observe that variation in average costs per employee from the first quartile to the third quartile is relatively low (around SFr. 5635 per year), whereas average price of capital in the third quartile is 24% higher than in the first quartile. This heterogeneity in the price of capital is mainly due to differences in new investments. In addition, NHs vary in output characteristics, i.e. the dependency index and the nursing staff ratio. Note, however, that 50% of NHs have a nursing staff ratio between 0.90 and 0.98. This is because the cantonal authority allows NHs to deviate from the value of reference by 10% only. Beyond this threshold, the RDPH intervenes to ask for an adjustment in the number of employees.

In Table 2.3 we provide some descriptive statistics for the variables of interest, calculated separately for the period before the change in the payment system (PRE) and the following period (POST). The fourth column specifies whether the variable mean has increased (+) or decreased (−). Finally, we report the results of a t-test on the probability of equal means across the two periods. Since cost savings can be achieved through a reduction in the number of staff, for the nursing staff ratio (Q_2) we test whether the mean value has decreased (one-sided t-test).

Variables	PRE (N=195)	POST (N=205)	Variation	H_0	P-value
AC	244.70	250.50	+	$\mu_{PRE} = \mu_{POST}$	0.013
Y	23153	24288	+	$\mu_{PRE} = \mu_{POST}$	0.184
Q_1	3.090	3.158	+	$\mu_{PRE} = \mu_{POST}$	0.047
Q_2	0.965	0.933	−	$\mu_{PRE} > \mu_{POST}$	0.000
P_l	80763	83278	+	$\mu_{PRE} = \mu_{POST}$	0.000
P_k	15049	15820	+	$\mu_{PRE} = \mu_{POST}$	0.000
K	66	69	+	$\mu_{PRE} = \mu_{POST}$	0.230

Notes: all monetary values are in 2005 Swiss francs (SFr.) adjusted by the national Consumer Price Index.

Table 2.3: Comparison of means (pre and post reform) for the main variables of interest.

The pre-post analysis shows a statistically significant but small increase in average costs (AC), from about SFr. 245 per resident day to than SFr. 250. The number of beds and the number of resident days remained pretty constant. As for output characteristics, the analysis shows that the dependency index has slightly increased while the nursing staff ratio decreased by 3% points. The increase in the dependency index may be due to the increasing demand of nursing home care over time and the shift of less severe residents to home care services. As expected, it shows that NHs did not respond to the change in the payment system by selecting healthier patients. Conversely, NHs may have responded to the change in the payment system by reducing the number of nurses per resident. The issue is discussed in more detail in section 2.5.2.

2.4.3 Identification strategy

At the bottom of any policy evaluation lays a missing data problem. In fact, an individual or a firm can always be observed only in one state: either in the program or not. The challenge of any evaluation analysis consists, therefore, in constructing an appropriate counterfactual. When the policy change occurs for only a few subjects under investigation or it is implemented gradually at different points in time, a battery of evaluation methods can be considered (Blundell and Dias, 2000; 2009; Nichols, 2007). Among the methods available for panel data, we find the difference-in-difference approach (DID), the matching estimator, the regression discontinuity designs (RD), selection models (also called control functions), structural models, the regression approach, and the counterfactual analysis. All these methods are motivated by the omitted-variable bias since correlation of policy identifying variables with other unobservable variables might lead to an incorrect assessment of the policy.

As pointed out by Blundell and Dias (2009), the choice of the most appropriate evaluation method relies on the nature of the policy change, as well as the research question and data availability. In our study, the policy change concerns all NHs in the sample at the same time. For this reason we can just observe the treated group before and after the policy change. Therefore, to measure the impact of global budget payment we exploit the panel properties of the dataset. We propose two different approaches. The underlying idea of the first approach (*Approach 1*) is to use information on different points in time for the same individual as own group of control (individual effects). We use a panel data model that controls for unobserved heterogeneity and includes a temporal dummy variable to capture the impact of the policy change. This strategy assumes that no other major event occurred over the period considered which affected the production costs of NHs. We are confident that, in our case, this assumption is not too restrictive. Firstly, because the NH sector is highly regulated and no other policy reform has occurred in the same period. Secondly, the resulting homogenous production process makes it relatively easy to compare NHs and reduces unobserved heterogeneity to negligible levels.[13] Consequently, time varying unobserved factors are not expected to have remarkable effects on the results. Finally, input prices and costs have been deflated with the Consumer Price Index. Hence, reduction in costs due to the recent economic recession should not be confounded with cost

[13] This is also confirmed by the similarity between fixed effects and random effects estimates.

savings generated by the new payment system.

We capture the impact of PPS on costs with a dummy variable equal to 1 for the years 2006-2010, the period where the PPS was in force, in addition to a general time trend capturing the impact of technical change on costs throughout the whole period. This is the approach adopted in many policy evaluation studies when the policy change affects all firms/individuals at the same time (e.g. Hatton, 2005; Nakahara et al., 2010; Narayana and Pengb, 2006; Rotte and Vogler, 1999).[14]

When adopting this identification strategy, particular attention needs to be devoted to the specification of the time trend. In fact, a misspecified time trend may partially capture the impact of the policy change. Hence, to explore the pattern of nursing care costs over time, we estimate a cost model where we replace the time trend with time dummies and drop the policy change dummy. The base year is 2001. In Figure 2·1 we report the estimated coefficients for time dummies as percentage change of total costs. From 2001 to 2005 total costs increase linearly. Afterward, i.e. under the PPS regime, total costs remain pretty constant.[15]

Assume the following general specification of the dummy variable in the total costs function in (2.8):

$$\ln\left(\frac{C_{it}}{P_{k,it}}\right) = \delta_0 + \sum \delta_s \ln X_{s,it} + \delta_d D + \delta_t t + \delta_{td} tD + \delta_i + v_{it}, \tag{2.9}$$

where X_s is the vector of explanatory variables in 2.8 excluding the time trend, D is the dummy that assumes value equal to 1 in the period of policy implementation ($2006-2010$), and 0 otherwise, and the error component ε_{it} has been split into an individual effect δ_i and a stochastic error term v_{it}.

The impact of the policy reform can now be measured in two ways, depending on how

[14] Remind that the pilot group cannot be used to apply a DID approach for three main reasons. First, treatment was not randomly assigned. Second, the treated group (pilot NHs) includes only few observations. Finally, the pilot phase was used to set up the new payment system and some rules changed afterwards.

[15] A different specification of the time trend shows that the inclusion of a squared term leads to overspecification and does not allow us to identify the impact of the policy change.

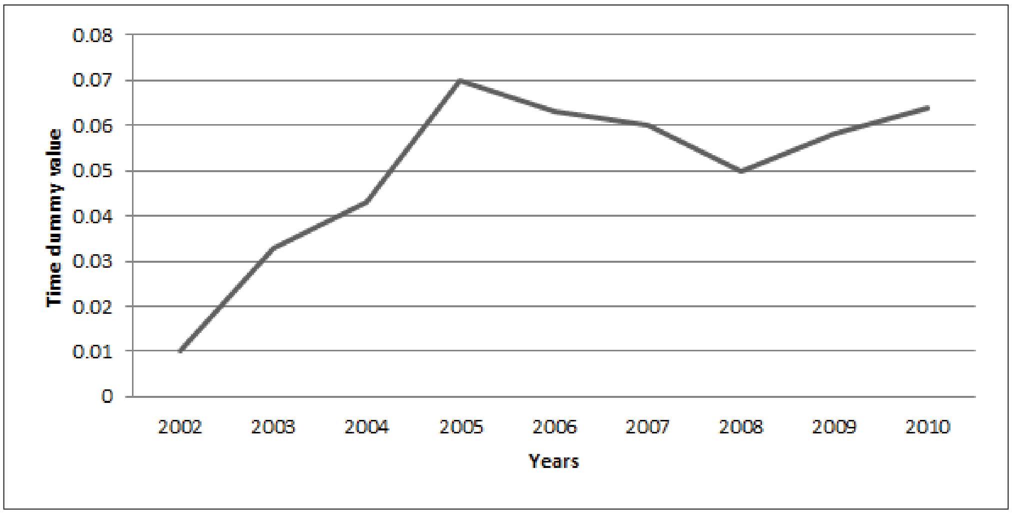

Figure 2·1: Estimated time dummies for the whole period 2001-2010.

the dummy variable is allowed to enter the cost function. By imposing $\delta_{td} = 0$, we restrict the attention to policy changes that affect only the constant term of the total cost function. In this case, dummy variable shifts are interpreted as the average impact of PPS on costs during the whole period $2006 - 2010$. Alternatively, if we allow $\delta_{td} \neq 0$, the impact of PPS can change over time, and additional information can be provided on the rate of costs increase. We refer to these two time trend specifications as the *restricted fixed-effects model* and the *unrestricted model.*[16] In the following section the results of these two model specifications are compared.

By identifying the policy change with a time dummy, we implicitly assume that in the absence of reform, total costs in the period 2006-2010 would have increased at the same

[16] A battery of specification tests was also performed. First, we checked whether the reform affected other coefficients by building interaction terms of each explanatory variable with the policy dummy (D) and did not find significant evidence. An alternative approach would consist of estimating two different models, one before the reform and one after the reform, and compare the estimated coefficients. However, this strategy allows individual effects to differ between the two periods, which is not desirable. Finally, we used the same approaches as in the first chapter of this thesis. We estimate several stochastic frontier models, such as the pooled frontier with Mundlak correction (Farsi at al., 2005) and the true random effect model. The impact of the reform was analyzed in two ways: first, we introduced the policy dummy into the deterministic part of the frontier, and second, we compared the calculated mean inefficiencies using the non-parametric Kruskal-Wallis test. All the model specifications and approaches used confirm the evidence that the new payment system reduced total costs.

rate as in the period $2001 - 2005$. Since economic growth may have an impact on the evolution of prices, for example wages, and therefore costs. Indeed, the Consumers Price Index decreased in the last years considered in the analysis. To control for changes in costs related to variations in the economic cycle, we then adjust cost and input prices for the Consumer Price Index.[17]

The second approach (*Approach 2*) uses the coefficients of the cost model based on the data prior the reform to predict the costs of each NH in the years afterward. The counterfactual is built by making predictions. In a recent study Horowitz (2007) makes use of predictions in the context of an energy saving program in the U.S. to investigate changes occurred in the electricity demand. The counterfactual is required to make the two groups comparable and purge the control group from different proneness to react to the policy change. This can be done by inserting the covariate means of the treatment group into the estimated model of the untreated. As explained, we estimate the cost function for the period prior the introduction of PPS ($t < 2006$) and use the coefficients ($\hat{\delta}_i$, $\hat{\delta}_s$ and $\hat{\delta}_t$) to predict costs of each NH i in each year t (nonlinear predictions) as follows:

$$\ln \widehat{\left(\frac{C_{it}}{P_{k,it}} \right)} = \widehat{\delta}_0 + \hat{\delta}_i + \sum \hat{\delta}_s \ln X_{s,it} + \hat{\delta}_t t \qquad \text{for } t \geq 2006. \tag{2.10}$$

The impact of the reform is computed as the difference between mean observed costs in logs and mean predicted costs in logs ($\overline{\ln C_{it}} - \overline{\ln \widehat{C}_{it}}$) in each year separately. The results of this approach are directly comparable with those of the *unrestricted model* of the first approach (*Approach 1*). We are clearly aware that this approach presents some limitations. For istance, the precision of the predictions is crucial for the assessment of the impact. However, we believe that this method can be used to check the robustness of the results obtained by the first approach.

[17] According to the cantonal law (RL 2.5.4.5), salaries and indemnities for public employees are adjusted using the national Consumer Price Index. Since labor costs represent the largest proportion of total costs (up to 85%), to deflate total costs and input prices by the CPI seems an appropriate choice.

2.5 Econometric estimation and results

2.5.1 Estimation approach

In order to choose the most adequate panel data model, we perform a series of tests on our NHs dataset. Since the likelihood ratio test rejects the null hypothesis of homoskedasticity ($\chi^2(40)$=161.46, P-value=0.000), heteroskedasticity-robust tests and estimation methods are considered. We examine the fixed-effect model (FE), the random effect model (RE), and the first difference model (FD) discussed in Nichols (2007) to create the counterfactual using observations on the same unit over time. These methods remove the bias due to unobserved characteristics that remain constant over time by adding individual-specific effects. Nevertheless, it is still necessary to control for the panel structure of the dataset, namely for errors correlated within groups (Cameron and Miller, 2010). If part of the bias is due to unobservable time-varying factors, our results may still be biased.

The difference between the FE estimator and the FD estimator consists mainly in the underlying assumption about the speed at which the policy reform affects the outcome. The FE estimates compare the mean outcome before the policy reform with the mean outcome in the period after the reform. Instead, the FD model assumes that the reform has a one-shot effect at the moment of its introduction. Therefore, the impact is fully captured by a jump in outcome in the year 2006. We rule out the FD model for two reasons. First, from a policy point of view the relevant question is what are the implications of the new payment system in the medium term. Second, the introduction of PPS involves a series of changes that need time to be understood, implemented and optimized.

Both the FE and the RE models include individual-specific effects that allow to control for any constant unobserved heterogeneity, but they differ in the way they consider these effects. In the FE model the individual effects are fixed parameters allowed to be partially correlated with regressors, thus accommodating a limited form of endogeneity (Cameron and Trivedi, 2010). In a policy evaluation study this property is of particular relevance. The sufficient condition for consistency of the FE model is $E[X_{s,it}(\varepsilon_{it} - \overline{\varepsilon}_i)] = 0$, i.e. the policy variable is allowed to be correlated with the persistent component of the error term - the unobserved heterogeneity - but not with deviations from the mean, $(\varepsilon_{it} - \overline{\varepsilon}_i)$ (Wooldridge, 2002). Three main requirements need to be satisfied when a FE model is applied. First, to avoid the so called incidental parameters problem, the time length should increase with the number of firms included in the sample. Second, the main variable of interest has to vary over time since the FE precludes the estimation of time-invariant regressors. Third, the percentage within variation of the variables of interest as with respect to the overall variation should be large enough to avoid imprecise estimates (Cameron and Trivedi, 2005). Instead, the RE model instead assumes that the unobservable individual effects are random variables distributed independently of the regressors, that is: $\delta_i \sim (\delta, \sigma_{\delta^2})$ and $v_{it} \sim (0, \sigma_{v^2})$, and the coefficients are estimated with the Generalized Least Square (GLS) method. Therefore, no correlation between the individual effects and the error term is permitted. The main disadvantage of the RE model is that the estimates are affected by the heterogeneity bias when the exogeneity assumption is not satisfied, and are, therefore, inconsistent.

In order to choose between the FE and the RE models we perform the robust version of the Hausman test using the artificial regression approach originally described in Arellano (1993).[18] The null hypothesis of regressors uncorrelated with the group specific effects is rejected at the 99% level ($F(14, 405)$=8.76, P-value=0.000). Also, the analysis of the within variation of each variable of the cost function shows that the percentage within variation over total variation is satisfactory for all variables of interest.

From literature on forecasting with panel data we know that the GLS estimator is the best linear unbiased predictor. However, as Baltagi (2008) shows, the FE predictor performs well and its accuracy is close to the GLS predictor in samples of comparative size to our dataset. Therefore, we choose the FE predictor also for our second approach, i.e. the

[18] The standard Hausman test assumes that the RE model is efficient. A comparison of the clustered and non-clustered standard errors show that this assumption is violated in our case. When this is the case, the robust Hausman test should be used. This approach consists in re-estimating the RE model augmented with the original regressors transformed into deviations from the mean.

counterfactual analysis. Confidence intervals for the mean difference are calculated to take into account the statistical properties of the coefficients. To avoid the retransformation problem (Ai and Norton, 2000; Manning, 1998), we predict the log of costs. Nonlinear predictions are allowed.

Standard errors are corrected using the cluster robust estimator based on Stock and Watson (2006).[19] The authors show that the cluster-robust estimator is preferred in FE models if serial correlation is expected, and it is reasonable to rely on asymptotic theory. In our sample, the number of clusters is satisfactory in order to rely on asymptotic theory for accurate inference (Kezdi, 2004). Also, each cluster contains a sufficient number of observations.[20]

2.5.2 Results

Through our regression analysis we are able to control for factors explaining variation in costs over time not related to changes in the payment system. As a consequence, we disentangle the general increase in costs from the impact of policy change. In Table 2.4 we present the estimated coefficients of the *restricted* and *unrestricted* FE models specified in the previous equation (2.9). The number of observations (N) and the model fit statistic R^2-*within* are also provided. The models explain about 92% of the variation in the data.

Since the cost model is in log-log form, the estimated coefficient of the policy dummy variable is interpreted as percentage change in total costs for small values of the coefficients, and semi-elasticity for higher values. The first-order coefficients are very similar in both specifications, therefore we focus the discussion on the *restricted* FE model. The output coefficient (δ_Y) measures the total costs elasticity with respect to output. A value lower than 1 suggests the presence of unexploited economies of scale in the NH sector. In our

[19] When dealing with panel data, the assumption of independently and identically distributed errors (iid) is mostly violated due to three main reasons: heteroskedasticity, within-cluster correlation and serial correlation.

[20] Kezdi (2004) states that a sample of 50 clusters is close enough to infinity for accurate inference if the number of observations for cluster is not too small. A cluster is considered small if it contains less than five observations per cluster (Rogers, 1994).

case it indicates that an increase by 10% in the number of resident-days would increase total costs by about 8.60%.

The parameter estimates of output characteristics (δ_{Q_1} and δ_{Q_2}) show a positive and highly-significant value meaning that total costs increase with patients severity and our quality indicator for the service provided, i.e. the nursing staff ratio. These coefficients can also be interpreted as cost elasticities. The case-mix coefficient (δ_{Q_1}) indicates that a 10% increase in patients severity increases costs by almost 2.4%. More important, a 10% increase in the nursing staff ratio (δ_{Q_2}) leads to a total costs increase of 4.3%. The input prices coefficient (δ_{P_l}) is positive and significant, meaning that the costs function is monotonically increasing in the vector of input prices. This coefficient provides information on the percentage of labor costs over total costs of a representative NH. The estimated share of labor costs is around 75%, which is very close to the actual sample mean (81%). Consequently, capital costs represent around 19% of total costs.[21]

The time trend parameter (δ_t) is highly significant and indicates that, on average, total costs have increased by almost 1% each year (1.9% in the unrestricted model). Increasing costs can be explained by increasing wages not associated to augmented productivity (Baumol and William, 1966), the adoption of more costly technologies or new procedures implemented in the whole sector due to regulation. The second-order coefficients show the percentage variation in first-order coefficients in response to a percentage variation in the regressors. We observe that many coefficients are statistically significant, supporting the use of the translog functional form.

Our main coefficients of interest are those related to the impact of the reform. In the *restricted FE model*, the impact of the policy change is captured by the dummy variable coefficient (δ_d), which measures the average impact of PPS over the whole period considered. As discussed above, costs increased by roughly 1% yearly from 2001. However, the

[21] The concavity condition is satisfied when the Hessian matrix (the second derivate of the cost function with respect to input prices) is negative semi-definite. Given that the squared term of the coefficient of the relative input prices is not statistically significant, the concavity condition is automatically satisfied over the entire range of observations.

Estimated coefficients	Restricted FE	Std. Err.	Unrestricted FE	Std. Err.
δ_Y	0.856***	0.056	0.845***	0.053
δ_{Q_1}	0.237***	0.040	0.244***	0.038
δ_{Q_2}	0.433***	0.041	0.523***	0.043
δ_{P_l}	0.743***	0.019	0.762***	0.019
δ_{YY}	0.406***	0.163	0.375**	0.144
$\delta_{Q_1Q_1}$	0.585***	0.106	0.499***	0.109
$\delta_{Q_2Q_2}$	0.761**	0.295	0.595**	0.289
$\delta_{P_lP_l}$	-0.009	0.087	0.045	0.079
δ_{YQ_1}	-0.183	0.148	-0.075	0.133
δ_{YQ_2}	0.251*	0.128	0.294**	0.121
δ_{YP_l}	0.118**	0.053	0.115**	0.051
$\delta_{Q_1P_l}$	0.626***	0.183	0.563***	0.171
$\delta_{Q_1Q_2}$	-0.060	0.272	0.057	0.259
$\delta_{P_lQ_2}$	0.028	0.184	0.054	0.054
δ_t	0.009***	0.002	0.019***	0.002
δ_d	-0.016***	0.007	0.082***	0.021
δ_{td}	-	-	-0.018***	0.003
δ_0	15.45***	0.006	15.42***	0.010
N	400		400	
R^2	0.913		0.924	

Notes: Significance levels: * = 10%, ** = 5%, *** = 1%.

Table 2.4: Results of the restricted and unrestricted fixed effect models.

negative and highly significant coefficient of the policy dummy suggests that the reform reduced mean total costs by 1.6% from its introduction in 2006. Concerning the *unrestricted FE model*, the impact of the policy reform is allowed to vary in each year and is given by the combination of changes in the intercept and slope coefficients of the time trend (δ_d and δ_{td}). The intercept of the time trend increases by 8.2%. However, the slope coefficient decreases by 1.8%. The effect of the reform on costs in different years is given by $\Delta TC = 0.082 - 0.018(t - 2000)$, where $t \geq 2006$. The effect is -0.026 in 2006, -0.044 in 2007, -0.062 in 2008, -0.08 in 2009 and -0.098 in 2010. Hence, in five years the new payment system led to a reduction in costs of roughly 9.8%.

Regarding the results of the counterfactual analysis, we report the annual impact of the reform on costs in Table 2.5 together with the 95% confidence intervals. The values shown are comparable to the joint estimation of coefficients δ_d and δ_{td} of the FE model and are indeed very similar.[22] Although the coefficients of the first years are not statistically significant, a clear pattern arises: -1.1% in 2006, 2.5% in 2007, -5.4% in 2008, -6.2% in 2009 and -7.5% in 2010. Figure 2·2 illustrates these results. On the y-axis we report the observed and the predicted logs of costs. Note that before 2006 observed and predicted costs are very similar, suggesting that the specified cost model is adequate. From 2006 the two cost curves diverge.

Year	Costs variation (mean)	CI (95%) Min	Max
2006	-0.011	0.050	-0.070
2007	-0.025	0.033	-0.082
2008	-0.054	0.005	-0.113
2009	-0.062	-0.002	-0.122
2010	-0.075	-0.013	-0.137

Table 2.5: Comparison between observed and predicted costs in the counterfactual analysis.

It is worth noticing that we estimated the impact of the policy change after controlling for quality, measured by the nursing staff ratio. As shown in the descriptive statistics, the nursing staff ratio has slightly decreased after the reform. However, the relationship between the nursing staff ratio and quality may not be straightforward. Although the number of nurses has decreased, it might be that their productivity has increased to preserve the quality of services provided to the residents. Improved managerial/organizational practices induced by the reform and hardly measurable, for instance, may have offset the small reduction in the nursing staff ratio. We remind the reader that the nursing staff ratio is periodically controlled by the cantonal authority who forbids NHs falling below a given threshold. Therefore, small reductions in Q_2 can be interpreted as a positive, cost-reducing effect of PPS.[23] This may also explain why our endogeneity test fails to reject the exogeneity hypothesis.

[22] By imposing linear predictions, the estimated value of the policy dummy is -0.053, which is higher than the result obtained with the *restricted* FE model. Nonlinear predictions allow us to model the impact of PPS in a more flexible way.

[23] We also performed the analysis without controlling for the level of nursing staff ratio. The estimated coefficient of the dummy variable was larger, as expected. We decided to keep Q_2 in the cost function to provide more conservative estimates of the impact of PPS.

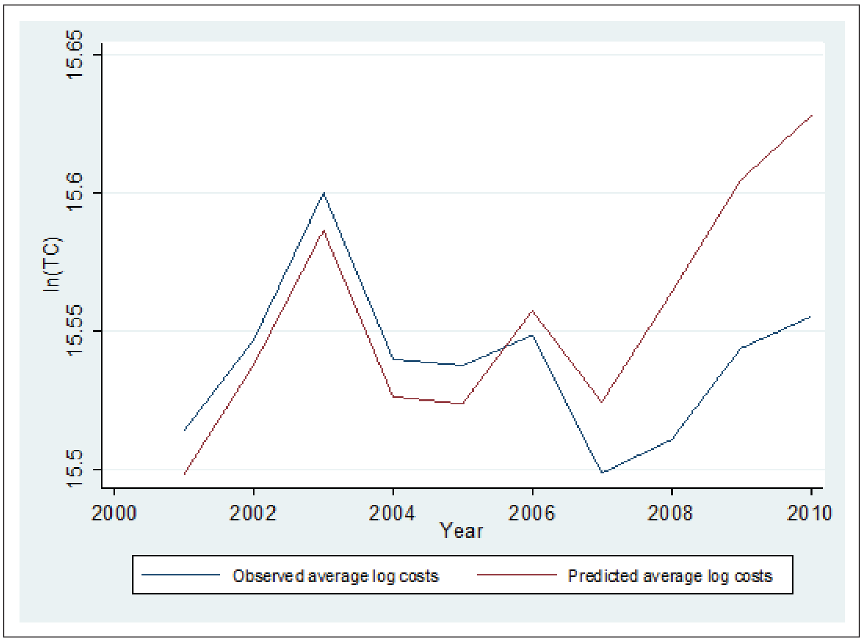

Figure 2·2: Graphical illustration of the counterfactual results.

2.6 Conclusions

Because of increasing healthcare costs and continuous pressure on public expenditures to provide healthcare and residential services to the elderly population, prospective payment systems may represent a promising way to enhance efficiency in NH care. Few empirical studies investigated the effects of PPS in nursing home care, mostly relying on U.S. data.

In 2006, a Swiss canton introduced global budgets to finance NHs. Through this study we provided new evidence on the impact of PPS in the form of global budgets on the performance of NHs.

Among important differences as with respect to the NH sector in the U.S., our context is characterized by nursing home services mainly provided by nonprofit firms as local mo-nopolies. We investigated the impact of PPS on the costs of providing NH care using a panel data set of 41 NHs observed for a 10-years period from 2001 to 2010. We assessed the impact of the policy change by means of two approaches. In the first, we included a time dummy to capture the change in time trend after the policy reform. In the second, we used the data 2001-2005 to estimate a cost function and predict costs after the reform. We interpreted the difference between predicted and observed costs as the policy impact.

Our analysis showed that the new payment system had a mild impact on costs after controlling for quality aspects using the nursing staff ratio. The pre-post analysis showed that the new payment system reduced costs by almost 9% after five years of policy implementation. Similar values were obtained in the counterfactual analysis, where the impact of the global budget after 5 years consisted of a reduction of 7.5% in total costs. The mild effect could be explained by three main reasons. First, as suggested by our theoretical approach, PPS changed incentives only for overfinanced NHs. Second, incentives to reduce costs were limited by the fact that NHs are free to use only part of savings (25%). Finally, NHs may be quite conservative in reorganizing work - including the reduction of working time or increased work intensity - that would improve cost efficiency.

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Appendix

Average costs per resident-day in pilot NHs are significantly lower than in non-pilot NHs in the period before the full implementation of the reform (Table 2.6), even though the difference is small.

Group	Mean costs (2001-2005)	Std. Dev.	t-statistic on mean difference
Pilot (N=28)	232.80	22.25	2.293***
Non-pilot (N=266)	244.70	22.00	

Notes: All monetary values are in 2005 Swiss francs, adjusted by the national Consumer Price Index.

Table 2.6: Average costs comparison between pilot and non-pilot NHs for the whole period.

In Table 2.7 we report the average costs of NHs in three different periods: the period prior the pilot phase (2001-2002), the pilot phase (2003-2005), and the period of full policy implementation (2006-2010). We also show the change in costs between two periods in absolute and relative terms (Δ). Average costs have increased in both groups between the first (1) and the second (2) period by about SFr. 20 (8.5%) for pilot NHs, and SFr. 10 (4%) for non-pilot NHs. Between the second (2) and the third period (3), average costs have slightly decreased for pilot NHs and remained pretty constant for non-pilot NHs. Since pilot NHs experienced a more remarkable increase in costs between the first period and the second period, the subsequent decrease of SFr. 6 (2.5%) suggests that they reacted more strongly to the new payment system than non-pilot NHs.

	2001-2002 (1)	Δ (2)-(1)	2003-2005 (2)	Δ (3)-(2)	2006-2010 (3)
Pilot NHs	220.50	20.50	241.00	-6.00	235.00
	(N=8)	8.5%	(N=12)	-2.5%	(N=20)
Non-pilot NHs	238.40	10.10	248.50	2.00	250.50
	(N=74)	4%	(N=121)	0.8%	(N=205)

Notes: All monetary values are in 2005 Swiss francs (SFr.), adjusted by the national Consumer Price Index.

Table 2.7: Average costs comparison between pilot and non-pilot NHs in different periods.

Chapter 3

The relationship between costs and quality in nonprofit nursing homes

3.1 Introduction

Ensuring good quality of care to nursing home (NH) residents is a major concern in many health care systems. Boosting quality levels must take into account cost containment measures, which are required to manage increasing health expenditures and ageing population. These twin objectives of the nursing home sector - high quality and affordable costs- calls for better understanding of the potential trade-off between costs and quality. Quality aspects need to be integrated in empirical evidence of NH costs. The literature on NH costs is extensive, but marginally addresses quality of care. Most of these studies do not include measures of quality. Some of them use imprecise or indirect measures, such as the number of deficiency citations, information about staffing or mortality rates. Others rely on modeling quality as a latent variable (Gertler and Waldman, 1992; Carey, 1997).

Failure to account for quality in cost functions is responsible for omitted variable bias (Braeutigam and Pauly, 1986). This bias is even more pronounced when comparing individual efficiency levels, as these techniques are particularly sensitive to model misspecification (Newhouse, 1994; Cremieux and Ouellette, 2001).

Donabedian (1988) conceptualizes the measurement of quality in health care in terms of three dimensions: Structure (S), Process (P) and Outcome (O). The SPO-framework is widely accepted in empirical analyses of quality. Failure to include information about these three dimensions of care are due to measurement deficiencies and limitations in data availability. Recently, the introduction of the Resident Assessment Instrument (RAI) in the U.S. and some European countries, started a comprehensive and multidimensional assessment of all NHs residents health status. These data, also called Minimum Data Set (MDS), are used to develop a battery of clinical indicators of quality that meet the taxonomy of the SPO model (Zimmerman, 1995). These indicators are categorized in two groups: indicators of quality regarding the process and indicators of quality regarding the outcome. As such, they offer a unique tool to measure and compare quality of NHs in different domains of care (Berg et al., 2012).

A positive relationship between costs and quality is generally expected when higher levels of quality can be provided only through more costly equipment or additional staff employment. However, adverse inpatient events may be costly to treat because they involve additional resource utilization for extra care. The relationship between costs and quality may therefore depend on the dimension considered. Better procedures are expected to increase costs, while prevention of development of adverse outcomes may actually reduce costs (Weech-Maldonado et al., 2006; Wodchis et al., 2007).

In this chapter, we investigate the relationship between quality and costs in nursing home care, taking into account refined quality measures. We improve the specification of the cost function for the production of NHs care services used in previous chapters by incorporating quality measures based on the taxonomy of the SPO-model. We also aim to disentangle the impact of different dimensions of quality on costs.

The remainder of the chapter is organized as follows: section 3.2 describes how quality for NHs services can be measured and presents the SPO-framework more in detail. Section 3.3 reviews previous studies on the relationship between costs and quality. In section 3.4 and 3.5 we report our data and describe the rationale behind quality indicators included in the following empirical analysis. We also detail the empirical strategy. Section 3.6 and section 3.7 respectively provide discussion of the findings and concluding remarks.

3.2 Quality

3.2.1 Definition and measurement of quality

No universal definition of quality exists in health research. The Institute of Medicine (IOM, 2001) states that "Quality of care is the degree to which health services for individuals and populations increase the likelihood of desired health outcomes and are consistent with current professional knowledge".[1] This definition has significantly influenced the literature on quality and is very much related to the paradigm of quality proposed by Donabedian (1988). His seminal article on the assessment of quality of care represents the foundation of modern quality assessment, providing a framework of reference with guidance validity. Donabedian proposed the so called SPO-framework. Structure is defined by the attributes of the setting in which care is provided, such as material resources (e.g. equipment), human resources (e.g. staffing levels) and organizational structure (e.g. payment system). Process refers to the activities of practitioners to give care, such as making a correct diagnosis and implementing the treatment accordingly. Outcome defines the change in health status of the patient. The success of this paradigm lies in its broad scope, which encompasses older concepts of quality. Table 3.1 shows how different measures of quality used in the literature fall within the dimensions of the SPO-framework. With the development of the quality indicators derived from the RAI, direct clinical measures of quality regarding process and outcome are available.

Structure	Process	Outcome	
		Objective	Subjective
Room size	Staffing information	Mortality rates	Resident satisfaction
Equipment	Mistakes rate	Hospitalization	Family satisfaction
Staffing levels	Deficiency citations	Quality indicators (RAI)	Deficiency citations
Nurse skill mix	Quality indicators (RAI)		

Table 3.1: Classification of quality indicators based on the SPO-framework (Donabedian, 1988).

[1] Other well recognized definitions are provided by the UK Department of Health (1997), the Council of Europe (1998), and the WHO (2000). For a detailed exposition of the most influential and known definitions of quality, see Legido-Quigley et al. (2008).

Only a few countries have adopted the RAI. Many use different systems to measure quality in the NH sector (Nakrem et al., 2009). Each measure of quality has advantages and disadvantages, which are discussed below. Some relatively old indicators (non-clinical) are still considered valid and are often combined in empirical studies with clinical quality indicators derived from RAI.

Previous studies attempt to capture NHs quality differences mainly using indicators of structure or indirect signals. Probably the most recognized indicator with current validity is the number of deficiency citations (Castle and Ferguson, 2010). Deficiency citations have the advantage of representing different dimensions of reduced quality but suffer from detection bias due to high variability in the use of citations among states/countries. Another important indicator that is employed extensively in the literature is the use of resources, in particular, information on staffing. While earlier studies focus on staffing levels as determinant factors (McKay, 1989; Farsi et al., 2005; Farsi et al., 2008), recent studies recognize the need to extend this dimension to staff characteristics, such as staff turnover, worker stability and skill levels (Castle and Engberg, 2005; Castle and Engberg, 2007; Dormont and Martin, 2012; Spilsbury et al., 2011), as well as willingness of leadership (Rantz, 2004). A recent systematic review of Bostick et al. (2006) shows not only evidence of association between higher licensed staff and quality, but also a significant relationship between staff turnover and quality indicators such as pressure ulcers, weight loss and functional ability.

Similarly, the advantages and disadvantages of the quality indicators based on the SPO model are discussed in Castle and Ferguson (2010). Structural indicators have the advantage of being easy to measure and data are often available. The disadvantage is that the presence of structural attributes does not imply its best use. Castle and Ferguson (2010) maintain that structural quality indicators are necessary but not sufficient. Indicators of process are usually easy to interpret as they inform on the provision of a particular treatment. Even in this case, it cannot be determined whether or not the provided treatment is appropriate. Finally, outcome indicators are of natural interest, as they measure the change in patients' health status. The main problem with these indicators is that it is extremely difficult to isolate the effect of care and changes in health, as the latter may be influenced by many uncontrolled factors.

Recently, interpersonal aspects of care to NHs residents received increasing attention. Residents' satisfaction seems to be a valid indicator with great potential even though it is not without limitations. People's reluctance to reveal their opinions and the inability of severe residents to understand and answer questions are among the most important.

3.2.2 Concerns about quality indicators

The recent development of clinical quality indicators has improved measurement of quality, but with some limitations. Firstly, due to the absence of a universally accepted definition of quality, the selection of quality indicators to include in empirical analyses is, to some extent, arbitrary (Castle and Ferguson, 2010). This is an issue because of the usually low correlation among quality indicators. Indeed, facilities with excellent outcomes in some dimensions may perform poorly in others. The choice of indicators may therefore affect the perception of NH quality. Secondly, detection bias occurs if higher quality NHs are the more vigilant in looking for and detecting quality issues (Mor et al., 2003). Since staff of the NH, rather than an independent authority, assesses residents health status, risk of detection bias exists. Thirdly, variation in clinical quality indicators may be due not only to changes in quality, but also in risk or to error (Arling et al., 1997). To cope with this issue, different risk-adjustment techniques are used. While previous studies of NH quality are limited to adjustment methods at the facility level (Nyman, 1988; Zinn et al., 1994; Zinn et al., 1993a), more recently risk-adjustment has been performed at the individual level. Different approaches include stratification, covariates model (Mukamel, 1997) and standardization (Zinn et al.,1993b). For some clinical indicators of quality that are considered particularly relevant in detecting the presence of problematic cases of quality shortcomings, no risk-adjustment is required. Among these are presence of daily physical restraints (Berg et al., 2002), dehydration and fecal impaction (Arling et al., 1997; Karon et al., 1999). The main issue of risk-adjustment techniques is that they may only partially capture the risk-factors of residents, resulting in biased estimates of quality coefficients may occur (Mukamel et al., 2008). To address this issue, instrumental variables techniques have been discussed (Angrist et al., 1993). Risk-adjustment is also of concern when risk-adjustment factors are themselves a function of quality. In these cases, quality scores could be over-adjusted, giving credit for poor quality (Mukamel et al., 2008). Finally, quality indicators are often criticized because they reflect a bio-medical perspective and neglect consumers' value of quality.[2]

3.3 Empirical evidence on the impact of quality on costs

Empirical models using non-clinical quality measures mainly focused on the impact of specific factors on costs, such as market structure, forms of organization, or reforms implemented in the NH sector. Quality measures are usually introduced as control factors. From these studies, some use staffing information (e.g. Crivelli et al., 2002; Farsi et al., 2005, 2008; Dormont and Martin, 2012; Konetzka et al., 2004) or deficiency rates (e.g. Harrington et al., 2001). Another strand of literature exploits determinants of quality variability. Factors considered include the impact of state regulations (Bowblis and Lucas, 2012), ownership form (Grabowski et al., 2013) and competition (e.g. Brekke et al., 2010; Castle et al., 2008; Forder and Allan, 2011; Grabowski, 2004; Starkey et al., 2005).

We focus our review on studies that try to disentangle the relationship between costs and quality using clinical indicators derived from RAI. Their main contribution is summarized in Table 3.2, with details on the choice of quality indicators, the empirical approach and the results obtained.

Mukamel and Spector (2000) is one of the first studies to investigate the relationship between costs and quality using the RAI-derived quality indicators. The authors estimate a variable cost function for NHs in New York State. Three indicators of outcome quality are included: activity of daily living (ADL), pressure ulcers and mortality. Regression-

[2] One possibility to include residents' voice it to use family and residents satisfaction scores (Sangl et al., 2007), however these data are not available.

Study	Quality indicators	Empirical strategy (Data)	Effects on costs
Mukaml and Spector, 2000	INC Functional decline	WLS (cross-sectional)	IU
	INC decubiti		IU
	Mortality		IU
Laine et al., 2005a	PR of pressure ulcers	SFM (cross-sectional)	+
	PR of weekly use of depressants		0
	PR of depression w/o treatment		0
Laine et al., 2005b	PR of depression w/o treatment	SFM (cross-sectional)	0
	PR of pressure ulcer		+
	PR of use of depressants		+
	PR of use of physical restraints		0
Weech-Maldonado et al., 2006	Worsening of pressure ulcers	2SLS (cross-sectional)	IU
	Mood decline		U
Wodchis et al., 2007	PR of physical restraints	RE,FE (panel-data)	-
	PR of use of depressant		0
	PR of urinary incontinence		+
	INC of urinary incontinence		U
	PR of skin ulcers		0
	INC of skin ulcers		-
	PR of pain		0

Note: INC=incidence (change), PR=prevalence, WLS=Weighted Least Square, SFM=Stochastic Frontier Models, U=U-shaped, IU=inverted U-shaped.

Table 3.2: Overview of selected studies investigating the relationship between costs and quality in NHs.

based risk adjustment is applied (Mukamel, 1997). Weighted ordinary least-squares is used to tackle the issue of different sample size in the calculation of the outcomes variables.[3] The authors report an inverted U-shaped relationship between costs and quality, although only few coefficients are statistically significant. The loss of statistically significance is attributed to high multicollinearity among higher-order terms of quality indicators. Due to the availability of only weak instruments, the endogeneity issue of quality is ignored.

An important contribution to the cost-quality relationship is provided by Laine et al. (2005a, 2005b) which implement Stochastic Frontier Models (SFM). In both studies, endogeneity of quality is not addressed. The first study (2005a) models a stochastic production frontier for the Finnish long-term care sector in 2001 where the dependent variable is specified as the case-mix weighted patient days and covariates include only input charac-

[3] The authors used the inverse of the squared root of the sample size as weights.

teristics. Ward characteristics and quality are modeled following Battese and Coelli (1995), i.e. technical inefficiencies are specified as a function of quality indicators. Quality is measured linearly by three continuous indicators: the prevalence of high-risk pressure ulcers, the prevalence of weekly use of depressants and hypnotics, and the prevalence of depression with no treatment. The latter two indicators are not risk adjusted. The prevalence of pressure ulcers is the only quality indicator significantly associated with technical inefficiency. The suggested relationship is that higher prevalence of pressure leads to higher technical efficiency.

Laine et al. (2005b) provide a similar cross-sectional analysis which shifts the focus from productive efficiency to cost efficiency. The analysis is performed using data at the ward level obtained aggregating individual-level data. The authors include quality indicators regarding process, the prevalence of depression without treatment and prevalence of pressure ulcers adjusted for risk, in the deterministic part of the cost frontier. Indicators of output quality, i.e. the prevalence of use of depressants and hypnotics and the prevalence of use restraints, are modeled following Battese and Coelli (1995). The mean values of the indicators over a three-years period is taken without risk adjustment. The underlying idea is to allow indicators of process quality to affect the production process itself, while outcome is restricted to have an impact on the level of inefficiency. The results show that a worse outcome in terms of higher prevalence of pressure is associated with higher costs, while poor process quality measured by the weekly use of depressants and hypnotics is associated with higher inefficiency. However, the impact of these quality indicators is relative low.

Weech-Maldonado et al. (2006) investigate the impact of quality on costs in U.S. NHs. Using cross sectional data from around 750 facilities, they test the inverted U-shaped theory by adding squared and cubic terms of quality. Quality is measured by changes in physical and psychological outcome indicators, i.e. worsening pressure ulcers and mood decline. Indicators are adjusted for risk using the covariates model (Mor et al., 1998). A weighted 2-stage least squares regression is estimated to address endogeneity of quality indicators.

Socio-demographic characteristics at the county-level as well as the presence of alternative service providers are used as instruments for quality scores. However, the validity of these instruments is not tested. The results show an inverted U-shaped relationship between costs and pressure ulcers. The opposite pattern arises for mood decline, showing that different indicators of quality may lead to different types of relationships.

Additional evidence based on data from Ontario, Canada, is provided by Wodchis et al. (2007). The authors estimate individual-effects models where total costs are regressed on output, labor price, some exogenous variables and quality indicators adjusted for risk using resident-level covariates model, with the only exception of prevalent physical restraint use. Heteroskedasticity, autocorrelation and endogeneity issues are discussed. However, due to the lack of a valid instrument, endogeneity is ignored. The analysis shows a negative relationship between costs and use of daily physical restraints, as well as worsening incontinence. Antipsychotic use, the prevalence of ulcers and the prevalence of severe pain are not statistically significant.

Most of the studies presented above find correlation between some quality indicators and costs. However, the association is weak and the approaches used are hardly comparable. The majority of them use cross-sectional designs and do not account for unobserved heterogeneity that may affect both costs and quality. Also, only few of them address the potential endogeneity of quality, and virtually no test is provided on the validity of the instruments.

In the following section we propose an empirical approach to investigate the relationship between costs and quality using data from Swiss NHs. As compared to previous studies, we are able to control for unobserved heterogeneity by exploiting a panel data set. Also, we address the potential issue of quality endogeneity and provide targeted tests to check the validity of the instruments on which endogeneity tests are based. Our specification of the cost model used in previous chapters is improved by including four clinical measures of quality regarding NH process and outcome.

3.4 Model specification and data

3.4.1 Choice of the quality indicators

To select the most appropriate clinical quality indicators for our cost analysis, we consider three strands of literature. First, we consult the medical recommendations on the pertinence of the indicators to reveal quality issues in NHs. Second, we consider studies on the technical requirements that quality indicators need to satisfy to be included in empirical analyses. And finally, we look at previous studies investigating the relationship between costs and quality using the quality indicators of Zimmerman (cfr. 3.3).

From the medical literature we take into consideration the discussion on the use of appropriate risk adjustment techniques, and consult the numerous lists of recommended indicators to use in benchmarking analyses of NHs (Berg et al., 2002; Morris et al., 2003; Rantz et al., 2004).

From the medical-statistical literature, we derive three main criteria that should be satisfied for the empirical analysis (Berg et al., 2002; Laine et al., 2005b): a relatively large variation in the quality scores, the absence of multicollinearity between the indicators and other variables, and a relatively large number of observations from which the quality indicators are calculated. The issue of the denominator is motivated by statistical properties since some quality indicators capture the onset of rare events. In these cases, the relevant question is whether the observed frequency of the event can be considered as a "true score", or it is driven by random shocks. Indeed, standard errors of rare events are large leading to problems in the comparison of quality among facilities. The minimum number of observations for benchmarking is 20 (Berg et al., 2002).

Finally, we consider previous economic studies exploiting the relationship between costs and quality with particular focus on the selection of the quality indicators included in the analysis (cfr. 3.3).

Based on these criteria, we selected 4 quality indicators from the 22 available in our dataset. The two indicators of process are the presence of antipsychotic use for low-risk residents (Q_{Antips}) and the presence of daily physical restraints use (Q_{Restr}). The two indicators of outcome include the prevalence of unexpected weight loss (Q_{Weight}) and the prevalence of severe pain (Q_{Pain}). Q_{Antips} is risk-adjusted based on the stratification approach, Q_{Restr} is a *sentinel indicator* and as such no risk-adjustment is required (Berg et al., 2002). For the two outcome indicators, no risk-adjustment is available. Due to lack of data at the resident-level, the covariates model cannot be applied. Finally, we control for time-invariant quality aspects regarding the structure of NHs through the econometric specification of the model (3.5).

3.4.2 Detailing the cost function

The model specification used in this chapter is based on the model specification used in the first chapter of this thesis. As previously discussed, in order to identify the impact of quality on costs, we include in the cost model four quality indicators derived from the RAI. Total costs are a function of: output (Y), the prices for labor, capital and material (P_l, P_k, P_m), the case-mix of residents (Q_1), a dummy for the institutional form equal to one when the NH is public-law and 0 otherwise (IF), the nursing staff ratio (Q_2) and the four indicators of quality ($Q_{Pain}, Q_{Weight}, Q_{Antips}, Q_{Restr}$). Finally we include a time trend (τ) to capture technological progress:[4]

$$C = f(Y, P_l, P_k, P_m, Q_1, IF, Q_2, Q_{Pain}, Q_{Weight}, Q_{Antips}, Q_{Restr}, \tau). \tag{3.1}$$

The price of labor is calculated as the weighted average wage of different professional categories employed in the NH (doctors, nurses, administrative and technical staff). We choose to include only one price of labor to avoid multicollinearity problems that typically arise with labor prices for different categories. The price of capital is calculated as the sum of mortgage costs, amortization and costs related to capital purchases divided by the

[4] In a non-competitive environment such as the Swiss one, there is no reason to assume that NHs minimize costs. In this case, the estimated costs function is a "behavioral cost function" (Evans, 1971) and can still be used to make a comparison among firms.

capital stock, which is approximated by the number of beds. The price for material and meals is computed by taking the remaining costs and dividing them by the number of meals provided each year. This item mainly includes costs for food, energy and administrative costs.

Additionally, we control for case-mix differences that may explain cost variability among NHs.[5] Q_1 is an index that measures average patients' assistance need by means of normal daily activities such as eating, personal care or physiological activities. This is calculated centrally on a yearly basis by the regulator. Patients are classified in one out of five categories according to their severity level. A value between 0 and 4 is assigned where higher values indicate more severe cases.

Q_2 is the nursing staff ratio, that is the ratio between the number of nurses employed in NHi and the number of nurses that should be employed according to the guidelines of the regulator (optimal amount of staff).[6] Because nursing care is a labor-intensive service, staffing levels have been recognized as a good indicator for quality (Bostick et al., 2006).

In addition to the nursing staff ratio, we include four additional indicators of quality derived from the MDS that measure the prevalence of adverse events, i.e. the prevalence of antipsychotic use (Q_{Antips}), daily physical restraints use (Q_{Restr}), weight loss (Q_{Weight}) and severe pain (Q_{Pain}).

For the estimation of the cost model in (3.1), we use a log-log functional form. This implies that the cost elasticities are not allowed to vary with output. When choosing the functional form, parsimony in the number of coefficients to be estimated is traded off against flexibility. A translog functional form as applied in the previous chapters of this manuscript, would require interacting all quality indicators with the production factors. The number of parameters to be estimated would explode to $\frac{(n+1)(n+2)}{2}$, leading to an

[5] In order to estimate a cost function, either the output is assumed to be homogenous or we need to control for service intensity and patients' characteristics (Birnbaum et al., 1981).

[6] As compared to other quality indicators related to staff levels, our indicator is conceptually different. The nursing staff ratio is the deviation from the optimal number of nurses that should be employed according to guidelines rather than the number of staff nurses employed.

important loss of degrees of freedom given our sample size.[7]

Input prices and total costs are divided by the material price in order to satisfy the homogeneity condition in input prices.[8] The log-log form of eq. (3.1) is:

$$\begin{aligned}\ln\left(\frac{C}{P_m}\right) &= \delta_0 + \delta_Y \ln Y + \delta_{Q_1} \ln Q_1 + \delta_{P_l} \ln \frac{P_l}{P_m} \\ &\quad + \delta_{P_k} \ln \frac{P_k}{P_m} + \delta_{IF} IF + \delta_{Q_2} Q_2 \\ &\quad + \delta_{Q_{Antips}} Q_{Antips} + \delta_{Q_{Restr}} Q_{Restr} \\ &\quad + \delta_{Q_{Weight}} Q_{Weight} + \delta_{Q_{Pain}} Q_{Pain} + \delta_t \tau + \varepsilon, \end{aligned} \tag{3.2}$$

where ε is the error term which may contain individual effects δ_i. The individual subscript i and the time subscript t are omitted for simplicity.

The estimation of the cost function in (3.2) is based on the assumption that output, input prices and quality are exogenous variables. In the case of the NHs included in the sample, output is likely to be exogenous because NHs have to accept all residents in a given catchment area and residents do not have free choice of facility. Also, the excess demand framework due to subsidized prices leads to occupation rates of about 100%. For the same reasons, case-mix is also likely to be exogenous. Moreover, reimbursement systems are linked to NH-specific case-mix, further reducing incentives to attract less costly customers. Input prices can be considered exogenous because NHs have to follow the guidelines imposed by the regulator.

As with respect to quality, it is important to distinguish between the indicator nursing staff ratio and the four clinical quality indicators derived from RAI. The nursing staff ratio is strongly regulated by the canton and a NH is not allowed to deviate too much from

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[7] In a preliminary analysis, we also tried to estimate: 1) a full-translog cost model and 2) an hybrid translog cost model. In the hybrid translog cost function the quality indicators were included only in linear form. The results of the full translog were not satisfactory, probably due to multicollinearity problems and the loss of degrees of freedoms. The results of the hybrid cost function were very similar to those obtained with the log-log functional form.

[8] The cost function is linear homogenous of degree 1 in input prices when a 10% increase in all input prices leads to a 10% increase in total cost.

the optimal staff size imposed by the canton. Therefore, we can exclude the presence of endogeneity.[9] The four clinical indicators of quality are instead not regulated and may therefore be endogenous. As we will see later in the empirical analysis, we try to address the potential endogeneity issue by using instrumental variables.

3.4.3 Data and descriptive statistics

To conduct the empirical analysis, we merge two datasets on costs and quality of long stay (chronic) patients NHs from a region in Switzerland (Ticino). The first dataset includes yearly resources use at the organization level extracted from the annual reports of NHs. It includes 45 NHs over a 10-years period, from 2001 to 2010. The second dataset contains information derived from the MDS on 22 quality indicators at the organization level for the period 2006-2010, excluding the year 2008. These indicators measure the presence of adverse events in a facility.[10] Due to missing values in the data set, no quality scores were available for three NHs for the years 2006 and 2007. We also exclude observations in which the denominator of the quality score is smaller than 20. This leads to a loss of other 14 observations. Complete data pertaining to 45 NHs observed over a 4-years period, 2006, 2007, 2009 and 2010 were used. The total number of observations is 163.

In Table 3.3 we provide descriptive statistics for the main costs and quality variables. Median values are not shown because of the similarity with mean values. The data show that on average a resident day costs SFr. 255. The difference between minimum and maximum costs is of almost SFr. 100. This may be due also to differences in output, as the number of resident days ranges between 30000 to more than 64000 days. Average case-mix of residents is 3.15, with important differences among NHs (2.38-3.83). The average price of labor and material is approximately SFr. 84000 and SFr. 9.60 respectively, and NHs are very homogenous in these respects. The price of capital shows higher variation, from SFr. 1500 to almost SFr. 17000. These differences are due to renovation or enlargement

[9] The Durbin-Wu-Hausman test performed using the lagged Q_2 as instrumental variable does not reject exogeneity at the 99% level.

[10] Unfortunately, data at the resident-level were not available.

investments. At the approximation point, the shares of capital-, material- and labor costs are 7%, 12% and 81%, respectively.

Variables	Mean	Std. Dev.	Min.	0.25	0.75	Max.
Average cost (SFr./Y)	255.73	21.48	213.01	242.03	268.83	359.64
Annual resident days (Y)	25434	10231	8955	19041	30128	64275
Average dependency index (Q_1)	3.15	0.30	2.38	2.95	3.38	3.83
Average labor price in SFr. per employee per year (P_l)	83680	4068	69415	81784	85776	97512
Average capital price in SFr. per bed (P_k)	6011	2320	1510	4552	7354	16914
Average material price in SFr. per meal (P_m)	9.60	1.49	6.85	8.73	10.12	16.11
Nursing staff ratio (Q_2)	0.93	0.07	0.74	0.88	0.97	1.12
Prevalence of antipsychotic use (Q_{Antips})	0.32	0.12	0.08	0.24	0.4	0.88
Prevalence of physical restraints use (Q_{Restr})	0.20	0.10	0.00	0.13	0.26	0.50
Prevalence of weight loss (Q_{Weight})	0.07	0.05	0.00	0.04	0.09	0.25
Prevalence of severe pain (Q_{Pain})	0.21	0.12	0.00	0.11	0.27	0.61

Notes: All monetary values are in 2005 Swiss francs (SFr.), adjusted by the national Consumer Price Index.

Table 3.3: Descriptive statistics of the main costs, inputs and quality variables.

Regarding the indicators of quality, the data show that, as expected, the nursing staff ratio is very close to 1, and little variation is present (0.74-1.12). On average, 32% of low-risk patients use antipsychotics, but in some NHs this value reaches 88% suggesting a serious problem in the NH sector. The average prevalence of daily physical restraints use is 20%, and ranges between 0 and 50%. The average prevalence of residents who lost weight unexpectedly is 7%, and this percentage ranges between 5 and 25%. Finally, on average, the prevalence of residents suffering from severe pain is 21%, but reaches more than 60% in some cases.

An interesting question is whether NHs that perform well in one quality dimension perform also well in the other quality domains. To answer this question, we compute the correlation among indicators (including the staff ratio) and Kendall's rank correlation coefficient (Kendall, 1955). The latter measures the similarity of the ordering of the NHs when ranked based on the scores of the quality indicators. Both measures indicate a very low correlation among quality indicators ($< 25\%$).

3.5 Methodology

The focus of this chapter is to analyze the impact of quality of process and quality of outcome on costs. We use a "classical" regression approach for panel data rather than stochastic frontier models. From the econometric point of view, the classical estimators to use with panel data are Ordinary Least Square (OLS), fixed-effects (FE) and random-effects (RE). The Breusch-Pagan test (1980) suggests the use of individual effects models ($\chi^2(1)$=32.18, P-value=0.000) as compared to the pooled model. Individual effects are used to capture quality regarding time-invariant structural aspects of NHs. The FE model treats the individual effects as fixed parameters. These are allowed to be partially correlated with regressors, thus accommodating a limited form of endogeneity (Cameron and Trivedi, 2010). Instead, the RE model assumes that the unobservable individual effects are random variables distributed independently of the regressors, that is: $\delta_i \sim (\delta, \sigma_{\delta^2})$ and $v_{it} \sim (0, \sigma_{v^2})$, and the coefficients are estimated with the Generalized Least Square (GLS) method. The Hausman test rejects the null hypothesis of no systematic difference in coefficients between the RE and the FE at the 5% level ($\chi^2(10)$=19.70, P-value=0.032). Given that the percentage of within variation of the variables of interest with respect to the overall variation is satisfactory, the FE estimates should be fairly precise (Cameron and Trivedi, 2005). Therefore, for the present empirical analysis the FE model represents the preferred estimator. The OLS and the RE estimates are presented for comparative purposes.

Standard errors are corrected using the cluster robust estimator based on Stock and Watson (2006) in all models. Stock and Watson (2006) show that the cluster-robust estimator is preferred in FE models if serial correlation is expected, and it is reasonable to rely on asymptotic theory. In our sample, each cluster contains a sufficient number of observations so that clustered standard errors would be preferred (Kezdi, 2004).[11]

Further, in order to take into account the potential endogeneity of quality, we also evaluate an instrumental variables approach. We consider both the Two-Stage Least Squares (2SLS) approach and the efficient Generalized Method of Moments (GMM) approach combined with the FE model. The GMM approach has the advantage of consistency in the case of arbitrary heteroskedasticity and shows higher flexibility than 2SLS, in particular to test the validity of the instruments. Both approaches come at the price of poor finite sample performance, in particular in the case of weak correlation between the instruments and the endogenous variable.[12] In this analysis, we prefer the GMM approach as it allows errors clustering for panel data and provides a battery of tests to check the validity of the instruments.[13]

A valid instrument must satisfy two requirements: the instrument z must be correlated with the endogenous variable x, $Cov(x, u) \neq 0$, and uncorrelated with the error term u, $Cov(z, u) = 0$. In the case of a single endogenous variable, the first condition is tested with a simple regression of z on x. A statistically significant coefficient provides evidence of the correlation between instrument and endogenous variable. In the case of multiple endogenous regressors, the *Shea partial* R^2 (1997) measure should be used, as it takes into account the intercorrelation among the instruments.[14] However, this does not exclude the possibility of weak instruments, which lead to a very high asymptotic bias.

The second condition can be tested when there are more instruments for an endogenous variable. In this case, the C-statistic, also called "difference-in-Sargan" statistic, can be

[11] Kezdi (2004) states that a sample of 50 clusters is close enough to infinity for accurate inference if the number of observations for cluster is not too small. A cluster is considered small if it contains less than five observations per cluster (Rogers, 1994). In the present case, the significance of the coefficients remain unchanged when standard errors are clustered as compared to not clustered.

[12] In particular, the efficient GMM approach may suffer from poor finite sample properties as the optimal weighting matrix of the efficient GMM estimator is a function of fourth moments, which require large sample size (Hayashi, 2000).

[13] A possible alternative to clustered standard errors for 2SLS estimates is bootstrapped standard errors. However, in the present case standard errors become so large, that the entire statistically significance gets lost.

[14] The F diagnostic for weak instrument for the joint significance of the instruments in first-stage regression does not recognize situations in which some instruments are good while others are weak.

used to test the orthogonality condition of a subset of instruments (Hayashi, 2000).

As shown in previous studies (Mukamel and Spector, 2000; Wodchis et al., 2007), it is not easy to find good instruments for quality. In this study, we rely on three hypotheses. First, the number of relatives visits exert pressure on the staff and management of the NH to keep an adequate level of quality. Second, the quality offered by the NH depends on the average quality offered by surrounding NHs. Third, the share of adults and elderly people living in the area of the NH exercise an indirect pressure on the quality offered by a NH.

We identify two variables related to the first hypothesis: the weighted average distance (traveling time) between the residents' location and the NH facility, and the weighted population density of the area served by each NH. The first measure captures the travelling time necessary for family members to reach the NH. When a NH serves residents from more municipalities, travelling times are weighted by the relative importance of the municipality in terms of population.[15] The same approach is used to calculate weighted population density. Population density is calculated as the ratio between the number of inhabitants and surface in hectare. The same weight is applied when more municipalities are served by the same NH. These variables are expected to capture residents empowerment through family members (voice). Higher population density and shorter travelling time are expected to increase the likelihood of being visited, as empirically shown by Dillmann et al. (2002).

For the second hypothesis, we build a variable to capture pressure from the presence of other NHs located in geographical proximity. For each year and NH, pressure is measured as the average score of each quality indicator of all NHs located in the vicinity. Vicinity is defined by the eight districts in which the region considered in this analysis is further divided.[16] The underlying motivation is that managers of NHs located close by affect each other's. Travel time or transport costs are increasingly used in the literature to

[15] Weights correspond to the relative percentage of people living in a municipality w.r.t. the whole catchment area of the NH. This approach works also in the case a NH serve only the population of one municipality, as in this case we measure the distance between the center of the village and the NH.

[16] The region considered in the analysis is further divided in 8 districts: Mendrisio, Lugano, Vallemaggia, Locarno, Bellinzona, Riviera, Blenio and Leventina. Given only few NHs are located in northern districts, Vallemaggia, Leventina and Blenio are pooled together.

investigate the impact of competition on quality (Brekke et al., 2010; Forder and Allan, 2011). Although in the present case competition is not direct, managers may still compete for other reasons such as reputation.

Finally, we include the percentage of young, adult and elderly population in the catchment area of each NH. Population structure is expected to capture the extent to which the population is interested and involved in issues relating to quality of NH services.

We also consider lagged values of quality indicators as a natural instrument. Lagged values are an attractive instrument due to the high correlation with the endogenous variable. Nevertheless, caution is necessary in the presence of serial correlation in the data, as this may invalidate the instruments (Angrist and Kruger, 2001). To test for autocorrelation in panel data set, we use the test developed by Wooldridge (Drukker, 2003; Wooldridge, 2002).

In Table 3.4 we provide some descriptive statistics of the instruments discussed:[17]

Instruments	Mean	Std.Dev.	Min	Max
Average distance from residents to NH	4.30	2.70	0.2	10.40
Population density in area served by each NH	10.62	14.30	0.13	80
Percentage young people	0.28	0.03	0.21	0.33
Percentage adults	0.26	0.02	0.21	0.34
Percentage elderly	0.20	0.04	0.12	0.30

Table 3.4: Descriptive statistics of instruments.

The average distance in terms of travelling time is about 4 minutes, with longest travelling time being almost 11 minutes. The average population density in each area served by the NH is of 10 inhabitants per hectare, but shows high variability reaching a peak of 80. The percentage of young-, adults- and elderly individuals is on average 28, 26 and 20, respectively.

[17] The descriptive statistics of the instruments for the second hypothesis are not shown as they are less informative.

3.6 Results

The estimation results are presented in Table 3.5. Standard errors are provided in parentheses. The statistics for R^2 and the number of observations (N) are provided at the end of the table.

The coefficients are very similar among the different panel models, with the exception of the output coefficient which is lower in the FE model. The OLS model does not consider the unobserved heterogeneity. The similarity of the RE and the FE estimates suggests a low correlation between individual effects and covariates. The results of FE combined with GMM (FE_GMM), which take into account the potential endogeneity of the quality indicators, are also very similar to the RE and FE estimates. Note that in this model we lose one year of observations due to the inclusion of lagged values for the quality indicators (N=113). The main difference w.r.t. the FE estimates is that the quality coefficients lose their significance. However, as we discuss later in more detail, the quality of our instruments is low. Therefore, the results obtained with FE_GMM could be biased.

In the following we interpret the results obtained with the FE model, as we believe that the bias induced by potential endogeneity of the quality indicators is less severe than the bias induced by weak instruments in the FE_GMM. However, due to the potential endogeneity of quality, all results should be interpreted with caution.

The output coefficient (δ_Y) is positive and smaller than 1, suggesting that an increase of 10% in output increases total costs by 7.5%. The coefficient of case-mix (δ_{Q_1}) shows that more severe patients are more costly to treat. The share of labor costs (δ_{P_l}) is estimated at around 90%, while the estimated share of capital is 6% (δ_{P_k}). These values are very close to the actual share costs, 82% and 7% respectively. The form of organization (δ_{IF}) does not seem to affect total costs, as discussed in the first chapter of the thesis.

Consider now the main variables of interest: the quality indicators. The nursing staff ratio (δ_{Q_2}) is highly statistically significant. As expected, the higher the relative number of staff working in a NH, the higher the costs. The coefficient is stable among all the

Table 3.5: Estimated coefficients of OLS, RE, FE, FE_GMM

	(1)OLS	(2)RE	(3)FE	(4)FE_GMM
δ_Y	0.875***	0.853***	0.751***	0.859***
	(0.017)	(0.019)	(0.046)	(0.110)
δ_{Q_1}	0.277***	0.254***	0.219***	0.299***
	(0.081)	(0.060)	(0.079)	(0.091)
δ_{P_l}	0.874***	0.910***	0.916***	0.923***
	(0.040)	(0.027)	(0.026)	(0.018)
δ_{P_k}	0.062***	0.059***	0.059***	0.067***
	(0.015)	(0.013)	(0.015)	(0.018)
δ_T	0.002	0.004*	0.005***	0.008***
	(0.002)	(0.002)	(0.002)	(0.003)
δ_{IF}	-0.009	-0.007	-	-
	(0.014)	(0.015)	-	-
δ_{Q_2}	0.485***	0.513***	0.480***	0.489***
	(0.089)	(0.069)	(0.071)	(0.074)
$\delta_{Q_{Pain}}$	0.076	0.061**	0.056**	0.055
	(0.046)	(0.028)	(0.027)	(0.067)
$\delta_{Q_{Weight}}$	-0.061	0.098**	0.102**	0.270
	(0.087)	(0.044)	(0.043)	(0.234)
$\delta_{Q_{Antips}}$	0.033	0.034	0.026	0.105
	(0.054)	(0.025)	(0.025)	(0.138)
$\delta_{Q_{Restr}}$	-0.119**	-0.071*	-0.064	0.087
	(0.048)	(0.040)	(0.042)	(0.125)
δ_0	-2.355***	-4.657***	-3.621***	-
	(0.439)	(0.328)	(0.541)	-
R^2	0.984	0.983	0.981	0.988
N	163	163	163	113

models. Regarding the other four indicators of quality, the magnitude and sign are pretty constant too, but the significance levels slightly change. Both individual-effects models show a positive and significant association between costs and the prevalence of weight loss ($\delta_{Q_{Weight}}$) as well as the prevalence of severe pain ($\delta_{Q_{Pain}}$). The use of daily physical restraints ($\delta_{Q_{Restr}}$) is instead associated with lower costs, but only weakly statistically significant. No association is found between the prevalence of antipsychotic use ($\delta_{Q_{Antips}}$) and costs.

The time trend (δ_T) is statistically significant, but its coefficient is very small. As shown in the previous chapter (Chapter 2), total costs have remained pretty constant since the year 2006 as a consequence of the introduction of global budgets.

We now present the statistics provided by the GMM approach to test the validity of our instruments, when all instruments discussed in section (3.5) are used. The *Shea Partial* R^2 statistics show that the percentage of variability in the quality indicators explained by the instruments is 10%, 17%, 7% and 12% for Q_{Pain}, Q_{Weight}, Q_{Antips} and Q_{Restr}, respectively. The endogeneity test does not reject exogeneity at the 99% ($\chi^2(4)$=3.081, P-value=0.544). Nevertheless, exogeneity of the 1-year lagged variable with respect to the error term tested with the *C-statistic* is rejected at the 5% level. This is also confirmed by the Wooldridge test for autocorrelation in panel-data (Wooldridge, 2002), which rejects the null hypothesis of no first-order autocorrelation ($F(1,44)$=7.074, P-value=0.011). Finally, the *Cragg-Donald F-test* based on the canonical correlation analysis,[18] does not reject that null hypothesis of weak instruments. Unfortunately, the statistics discussed above suggest that the quality of our instruments is not satisfactory. Therefore, exogeneity of the quality indicators cannot be demostrated empirically.

[18] When more endogenous variables are present, weakness is tested by looking at the association between all endogenous variables and all instruments, after controlling for all other exogenous variables included in the model (Hill, Griffiths and Lim, 2011).

3.7 Conclusions

To ensure good quality of long term care while keeping costs under control, a better understanding of the relationship between costs and quality is needed. In the NH sector, quality improvements represent a main concern since the ageing of the population is putting the system under financial pressure.

In this chapter, we investigated the relationship between costs and quality according to the SPO-framework developed by Donabedian (1988). We used the recently published data on quality indicators for Swiss NHs derived from the RAI. In addition to the nursing staff ratio, we considered two additional indicators of process quality, i.e. the use of antipsychotics for low-risk residents and the prevalence of daily physical restraints, and two indicators of the outcome quality, i.e. the prevalence of weight loss and the prevalence of severe pain. As compared to previous studies, we estimated an individual effects model based on a panel data that allowed to control for unobserved heterogeneity. We estimated a log-log total costs function and included quality indicators of process and outcomes as covariates. The empirical analysis showed some evidence of a positive relationship between clinical indicators of quality regarding outcomes, the prevalence of severe pain and the prevalence of weight loss, and total costs. We also found some evidence that higher prevalence of daily physical restraint use is associated to lower costs, even though the relationship is weakly significant. The use of antipsychotics is positively related to costs, although not significantly. Finally, staffing levels are strongly correlated with costs. However, our empirical results may be biased due to the potential endogeneity of quality.

From a policy point of view, a correlation between costs and quality may suggest that quality aspects should be incorporated in funding schemes designed for nursing home care. Accounting for this correlation may allow the regulator to combine quality and costs objectives and provide appropriate incentives through improved financing schemes for NHs.

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